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Simulating business team assembly with network models

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Abstract

Many business organizations utilize team structures as a way to organize their personnel and integrate the diverse backgrounds and competencies of their employees. As a result, team assembly strategies are important to an organization's productivity and should be evaluated by managers. This thesis utilizes network modeling and simulation to explore and assess various team assembly strategies that incorporate the concept that some people energize their teammates, whereas others de-energize them. Research in this area of energy networks studies the impact that energizing and de-energizing employees have on the performance of their co-workers and, as a result, the success of business organizations overall. Energy networks have been studied with network analysis, but very little if any research has focused on simulating energy networks so the model in this thesis includes energy as a key attribute to consider when assembling teams.

An existing team assembly model is adapted to include an energy rating component for team members and used to investigate two realistic strategies for team assembly based on different energy motivations: organization based on similar energy rating and organization with respect to various team composition constraints. Four different policies are modeled and simulated for the second strategy. Team assembly based on similar energy rating yields high frequencies of occurrence of both energizing and de-energizing teams, while the three policies aimed at achieving teams with balanced energy, mostly energizing, and mostly de-energizing accomplish their respective goals. The policy aimed at integrating a diverse range of energy ratings yields variable results. Analyzing the simulation results elicits recommendation for managers about the energy-focused strategies and policies explored.

Chapter 1: Introduction

Many business organizations utilize team structures as a way to arrange their personnel and integrate the diverse backgrounds and competencies of their employees (Cross, Ehrlich, Dawson, & Helferich, 2008). As a result, the construction of business teams is important to an organization's productivity and should be evaluated by managers. Effective team assembly is a balancing act, and managers need to be aware of how to put together teams that meet the objectives they have set and fulfill the competencies they are emphasizing.

The most accurate model of a business network will focus on the unique individuals within the organization, which facilitates a more direct representation of different organizational units and includes the diverse characteristics and relationships of each employee (Anderson, 1999). In many cases, managers want to ensure that teams have a balance of certain employee qualities and capabilities or focus on strategically placing a specific competency within or across teams. Determining efficient methods for modeling and simulating team assembly strategies is an important problem within the realm of organizational theory and strategic management because team structures are likely to persist in business organizations in the future.

A nascent approach to studying the dynamics of teamwork in business is by analyzing employee energy networks. Energy, in this context, is a positive feeling of enthusiasm in workers, as well as an expression that can be perceived by others, constituting a powerful dynamic feedback mechanism in organizations and teams (Quinn, 2007). Energy networks seek to illustrate the affective impact that co-workers have on one another in interactions, that is, whether an employee increase or decrease enthusiasm in others (Cross, Baker, & Parker, 2003). In many studies, this boils down to co-workers answering the question, “When you interact with this person, how does it typically affect your energy level?” (Cross & Parker, 2004, p. 4). An employee’s energy can have a major impact on forging positive relationships and achieving success in team environments, so identifying energizers and de-energizers in a business network is a valuable component of effective team assembly (Quinn, 2007).

Energy networks have been studied with network analysis, but very little if any research has focused on simulating energy networks. The simulation model in this thesis includes an energy component for each employee and seeks to help managers evaluate realistic strategies for team assembly that focus on energy. The network model takes an agent perspective that preserves the unique characteristics of the individuals in an organization and serves as an initial step towards integrating energy networks into a more influential modeling approach called agent-based modeling and simulation (ABMS). ABMS facilitates simulations of multiple unique entities that each possess individual traits as well, but also act autonomously to make decisions and interact with other agents (Gilbert, 2008). ABMS is a powerful and natural framework for complex systems that appears to have the potential to make a major impact on organizational simulation and strategic management in the future.

The simulation model considers two strategies for team assembly in business organizations:

1. Team assembly based on similar energy ratings.
2. Team assembly with respect to team composition constraints.

Managers could formulate a number of constraints for team composition, so the following four policies are considered and modeled for the second strategy:

2a. Managers want to balance the energy level of teams by including both energizing and de-energizing employees.

2b. Managers want teams to include at least one de-energizing team member, but otherwise want energizing workers.

2c. Managers want teams with mostly de-energizers to include at least one energizing worker to raise the average energy of the team.

2d. Managers want a high level of variability in the energy ratings of team members, so at least one team member with each energy rating must be present in a team before incumbents with repeat energy ratings can be added to a team.

Chapter 2 in this thesis provides background relevant to the research problem. Information on the topics of business teams, network theory, social network analysis, energy networks, an agent perspective, and agent-based modeling and simulation will be presented. The later chapters focus on exploring various strategies for team assembly with employee energy incorporated into a network simulation model. Chapter 3 provides a detailed description of the baseline model, the adapted model, and the modeling methodology. Chapter 4 explains how the model was verified and validated. Chapter 5 presents the simulation trials conducted and describes model results. Chapter 6 discusses findings and conclusions, recommendations for managers, and avenues for future work.

Chapter 2: Background

The simulation model developed for this thesis focuses on a business team assembly framework that incorporates employee energy ratings as the key factor in determining how teams are formed. A number of different research areas influence and inform the adapted simulation model. This chapter will present background on business teams, network theory, social network analysis, energy networks, an agent perspective, agent-based modeling and simulation, and the baseline model adapted in this thesis.

Business Teams

Many organizations implement teams as a way to arrange their personnel for projects or day-to-day work (Cross, 2000). Team structures can incorporate diverse perspectives and experience into a project by bringing together people from different departments, specialties, and backgrounds (Cross et al., 2008). New ideas and fresh viewpoints can lead to a larger pool of knowledge from which to draw, a more diverse collection of opinions to consider, and a more robust check on decision-making processes to prevent costly mistakes and ensure that the best choices are made (Cross, 2000). Teams also help maximize available knowledge in an organization by forging inter-departmental relationships between employees who otherwise might not work together, allowing co-workers to learn new skills from one another as a result. The benefits that many business organizations reap from implementing teams seem to justify their use and indicate that they will likely persist in the future.

There are often competing dynamics in business teams, however, that can stifle their effectiveness. Members of teams are interdependent and must work together towards a common goal, accentuating the need for trust and dependability (Ioerger, 2003). Project teams are dynamic and vary in terms of structure, duration, and distance, so continual communication is a critical component to effective information exchange, conflict prevention, and mutual awareness (Ioerger, 2003). While teams are often assembled as a means of promoting diversity of ideas and skills by bringing together co-workers with different backgrounds, it can be difficult to find the ideal balance of team member perspectives (Guimerà, Uzzi, Spiro, & Nunes Amaral, 2005). Promoting diversity in teams as they are assembled can sometimes come at the expense of the comfort that many people feel working with previous collaborators, relationships that often produce increased efficiency and productivity (Guimerà et al., 2005).

Effective team assembly is a balancing act, and managers need to be aware of how to put together teams that meet the objectives they have set and fulfill the competencies they are emphasizing. The study of team assembly in organizations has been enhanced by the development of tools like network theory, social network analysis, and modeling and simulation that allow managers to obtain a better picture of an organization's personnel. Managers can use these tools to analyze different possible organization designs focusing on specific qualities and competencies in team members to determine effective team assembly strategies given organizational goals.

Network Theory

A network is a collection of connected entities, evident in a diverse array of systems ranging from biological to technological to social (Watts, 2003). Networks are the focus of a discipline that has gained renewed applicability with the increasing complexity of systems in the world (Barabási, 2005). Network theory promotes a network perspective toward viewing systems, which entails attention to the connections between components and concentration on explaining how dynamic networks develop and evolve (Newman, Barabási, & Watts, 2006). General conclusions about complex systems can be obtained because the associations and interactions of individual nodes (the connection points in networks) aggregate and often generate patterns of emergent collective behavior (Newman et al., 2006; Watts, 2003). Increased computing power and more sophisticated simulation technology enables researchers to analyze millions of individuals and their connections in order to better understand relationship dynamics and collective behavior in the many instances of networks in the real world (Barabási, 2005). Thinking about personnel in terms of networks can give managers a clearer view of the interdependencies that exist within a business organization. An understanding of the larger network context of a business organization is also valuable for managers when assembling teams using the specific application of social network analysis.

Social Network Analysis

Social network analysis (SNA) is a technique for mapping and analyzing relationships between people to develop an understanding of how these relationships impact an organization or system (Cross et al., 2003; Cross et al., 2008). Social network analysis is focused not on increasing interactions between people in general, but on increasing productive interactions and reducing unproductive ones (Cross et al., 2008). The results of SNA can be used to aid managers in effectively designing an organization and positioning employees in such a way that maximizes the goals of the organization. A social network perspective for approaching organizational design can help managers emphasize a specific competency by identifying key individuals with it and spreading those workers across the entire network or throughout project teams (Cross et al., 2008).

Social network analysis often results in network diagrams of current and possible future organizational designs and team compositions. Managers can focus on specific characteristics and competencies for employees in these diagrams, but there is often not enough time to analyze the many different combinations of team organization that are possible. Simulations build on the results of SNA and can be used to more efficiently produce versions of the many possible paths that a business network or team could take. The network simulation model in this study will explore various approaches for assembling teams by focusing on the energy characteristics of team members.

Energy in Organizations and Teams

Analyzing employee energy networks is a nascent approach to studying teamwork dynamics in business. Energy is expressed in two ways in a business environment. First, energy is a feeling of enthusiasm that a person has about the projects s/he is working on or the people s/he is working with (Cross et al., 2003; Quinn, 2007). Energy can manifest itself as an emotion, a mood, or an overall demeanor (Cross et al., 2003). This influences the second aspect, in that a person's energy is also an expression that others perceive in a certain way via various interactions. A person's level of energy can affect the way others feel about a project, idea, or collaboration in a positive, negative, or neutral way (Cross et al., 2003; Quinn, 2007). Energy is often referenced in terms of an energizing conversation or interaction, in which one person's energy causes a co-worker to become "mentally engaged, enthused and willing to commit effort to possibilities arising from the discussion" (Cross et al., 2003, p. 51). Since energy is both a feeling of enthusiasm in people and an expression that can be perceived by others, energy constitutes a powerful dynamic feedback mechanism in organizations and teams (Quinn, 2007). Energy is intangible and often difficult to define, but many managers recognize that it is an integral part of forging positive relationships and achieving success in team environments (Cross & Parker, 2004; Quinn, 2007).

The Impact of Energy on Teams

The ability to engage and energize others is often a critical characteristic needed for a member of a business team to succeed (Cross & Parker, 2004). People in an energy network are classified as energizers, de-energizers, or neither. Energizers are influential workers who create enthusiasm for their work and, in the process, impact the energy level of their co-workers in a positive way (Cross & Parker, 2004). Energizers are usually focused and trustworthy, gaining the respect of co-workers and forging positive working relationships with those around them as a result (Cross et al., 2003). De-energizers, conversely, tend to deflate the overall enthusiasm of co-workers (Cross et al., 2003). De-energizers could be unfocused, overly pessimistic, or otherwise difficult to work with, persisting in unconstructive actions that negatively affect the energy and progress of those around them (Cross et al., 2003).

When subjective employee evaluations and objective performance data are cross-referenced with energy networks, it has been demonstrated that employees deemed as energizers by their co-workers tend to be higher performers (Cross et al., 2003). An energizer is not necessarily a person with overwhelming energy or one who feels the need to “run the show.” Energizers, rather, are enjoyable and easy to work with, often leading others to be more willing to provide them with necessary information or assistance in solving a problem (Cross & Parker, 2004). This gives energizers an advantage by maximizing their pool of resources for completing tasks and projects. Co-workers will also be more likely to seek out energizers for their own information needs, giving energizers the ability to make a huge impact on learning throughout the organization simply by their energizing interactions (Cross et al., 2003; Cross & Parker, 2004).

Employees can often become energized by an interaction where there is a feeling of opportunity, optimism, progress, and engagement (Quinn & Dutton, 2005). People want the chance to contribute meaningfully to something in their work and are more optimistic about realistic opportunities (Cross et al., 2003). Energizing workers are inspiring without being overwhelming and motivate those around them by concentrating on project possibilities rather than potential obstacles (Cross et al., 2003; Cross, Linder, & Parker, 2006). Energizers are able to create excitement about and elicit support for their ideas, making them more likely to be put into action (Cross & Parker, 2004). In addition, high performers are drawn to working with other high performers (Cross et al., 2003). This coupled with the idea that people are more likely to put in effort for energizers in general shows how energizers have the ability to raise the overall level of performance of those around them (Cross & Parker, 2004). The combination of these characteristics produces an archetypal leader that is able to energize teams, stimulate productivity, and complete tasks and projects (Cross & Parker, 2004). Energizers are a major driving force behind performance, and by extension success, in an organization.

Energy Network Analysis

Researchers use energy networks as a way to investigate and illustrate the impact that employees have on one another in terms of energy level (Cross et al., 2003). Social network analysis can be utilized to determine the impact of relationships within energy networks. An SNA based on energy often focuses on co-workers considering the question, “When you interact with this person, how does it typically affect your energy level?” (Cross & Parker, 2004, p. 4) and reporting their answer on a scale of one to five (where one is strongly de-energizing, two is de-energizing, three is neutral, four is energizing, and five is strongly energizing) (Cross & Parker, 2004). This again shows the dual nature of energy: an employee has some level of enthusiasm that is perceived by others and influences their respective levels of energy. The results of an energy survey can help managers understand the extent to which each employee energizes or de-energizes those around them via interactions (Cross et al., 2006). Integrating this information into a network diagram can help managers identify which employees occupy critical points in the energy network and where energy is lacking in their organizations (Cross et al., 2006).

Furthermore, by identifying the energizers and de-energizers, managers can strategically place them in positions within the network that maximize energy and connectivity in the organization. In one energy network study, researchers limited the network diagram to only those people who were deemed de-energizers by their co-workers and found a significant drop-off in connectivity in the network (Cross & Parker, 2004). It was evident that employees did not want to work with de-energizers and sought to avoid connections with them as much as possible (Cross & Parker, 2004). Since energizers create enthusiasm about their work and have a profound impact on co-workers, positioning them in a way that bridges otherwise disconnected groups within a network may be an effective strategy for managers to maximize their impact on an organization (Cross & Parker, 2004). Simulating energy network analysis results can make it easier to examine the many possible organizational designs and team compositions that can arise in a business network.

Overall, energizers seem to have an overwhelmingly positive impact on an organization. There are two major results that managers should take away from these findings. First, it is valuable to have well-qualified energizers in an organization. Second, it is important to determine who the energizers within an organization are and how to strategically place them across a business network and within teams to maximize their positive impact on organizational productivity. This is the focus of the simulation model in this thesis, which takes an agent perspective in exploring how various strategies for team assembly affect the average energy of teams.

An Agent Perspective

The most effective way to model and simulate organizations is from an agent perspective, which provides a direct representation of actual organizations and preserves the unique, individual characteristics of each worker (Gilbert, 2008). Network simulation models that take an agent perspective are valuable to the areas of organization theory and strategic management because organizations can often resemble complex adaptive systems (Anderson, 1999). A complex adaptive system is a collection of interacting components, each with its own set of rules for action and adaptation that impact the overall behavior of the system (Macal & North, 2007). Organizations often feature a set of interdependent individuals, departments, and other associations that influence the structure of the organization and the collective behavior of its constituent parts (Anderson, 1999). An agent perspective to organizational simulation affords managers realistic depictions of their personnel and business networks because the heterogeneity of the individuals involved can be modeled in the distinct agents in the simulation.

A manager can use a simulation model from an agent perspective to test various organizational design scenarios in order to better understand their effects on specific strategic objectives (Bonabeau, 2002). Decision-making in business is complicated because there are a seemingly endless number of possible options to consider in order to make a reasonable choice (Macal & North, 2007). A multitude of variations of a network simulation focused on specific characteristics and competencies can be completed to reveal the many potential paths that an evolving business network might take (Anderson, 1999). The resulting set of extensive potential outcomes is more comprehensive than those that would have been considered otherwise, eliminating the need to spend additional time and resources on brainstorming more scenarios (Macal & North, 2007).

Agent-Based Modeling and Simulation

An agent perspective is important and useful for organizational simulation, but a more powerful application is the method of agent-based modeling and simulation, where agents have unique characteristics but can also make independent decisions and interact with other agents (Bonabeau, 2002). ABMS is a computational method in which autonomous agents individually assess their current state based on local information then determine what their next action will be based on a set of rules that defines their behavior in various situations (Bonabeau, 2002). Agents can represent individuals or collective entities, such as groups or organizations, and each agent in a simulation model is discrete with an individual set of attributes and behavioral rules (Gilbert, 2008; Macal & North, 2007).

The ABMS approach “provides a natural description of a system” (Bonabeau, 2002, p. 7281), such that each person involved in a real-world social system can be represented individually rather than being amassed into a population of similar types. Breaking down component characteristics to the fundamental level of a single agent allows an agent-based simulation model to facilitate interactions between entities within some defined environment (Gilbert, 2008). The environment, or interaction topology, can be a spatially explicit area (representing a physical space) or a non-spatial structure of relationships (like a network, similar to what is used in the simulation model in this thesis) (Gilbert, 2008). The repeated execution of independent agent interactions allows agent-based models to reveal emergent collective behavior through the actions of individual components (Macal & North, 2007). Agent-based model simulations are realistic because overall system behavior is decentralized and never defined, occurring instead as a result of the interactions of individual agents (Borshchev & Filippov, 2004).

Agent-based simulations allow managers to analyze potential interactions and connections that could occur between co-workers within business organizations in order to explain the evolution of their relationships, which appears to be a valuable tool for organizational theory and strategic management in the future. The simulation model in this thesis lacks the agent characteristics necessary to be considered ABMS, but is intended to be an initial step toward a future agent-based team assembly model that will be valuable to managers in actual organizations as far as organizing their personnel.

NetLogo Modeling Environment

Though the simulation model in this thesis is not agent-based, it does take an agent perspective towards business team assembly. As a result, an agent-based-specific modeling environment called NetLogo is used. Agent-based modeling environments provide the tools necessary to build, run, and analyze agent-based models and simulations in a single software program usually designed for novice users (Gilbert, 2008; Macal & North, 2008). NetLogo was developed in 1999 by Uri Wilensky from the Center for Connected Learning (CCL) at Northwestern University (Wilensky, 1999). NetLogo was chosen because it is designed to be easy to learn, intuitive to use, and flexible enough to create agent-based models and simulations for a number of different applications including networks (Macal & North, 2007). It also provides a model library with many sample models from various subject areas, including the baseline team assembly model from which the simulation model in this thesis is adapted.

Baseline Team Assembly Model

The simulation model in this thesis is adapted from the sample NetLogo team assembly model developed by Wilensky (2005), based on research by Guimerà et al. (2005), that explores the relationship of team formation mechanisms and collaboration networks. In this baseline model, project teams are assembled at each time step by combining incumbents (workers that have previously been on a team) and newcomers (workers that are added to the network at the time a team is formed). The model structure is based on the premise that a preference for either incumbents or newcomers in team assembly will affect the overall network structure in distinct ways. As in the real world, teams are a subset of workers formed from a larger pool that includes other potential team members with various characteristics and established relationships.

The baseline model operates from an agent perspective as individual agents with unique attributes and behavioral rules exist within a network. The baseline model, however, uses a relaxed definition of agents that precludes it from being an agent-based model. Nigel Gilbert outlines four characteristics that agents in ABMS should possess: perception, performance, memory, and policy (Gilbert, 2008). Agents in the baseline model have a memory of the other agents with which they were previously members of the same team and policy in terms of the team assembly rules for determining which agents will be added to a team. The perception and performance characteristics, however, are incomplete in the baseline model agents. Agents are able to perceive previous collaborators, but do not evaluate their environment beyond that. The performance characteristic is not fulfilled because an agent does not decide to start a team based on some local information and communicate with other agents to invite them to join. Rather, the model framework abstracts this process to simply produce an assembled team at each time step composed of agents available based on parameter settings, programmed rules, and randomness. Agents do not have a choice in deciding which specific individuals are added to a team or whether they would like to join a team when chosen; agents are just selected and added regardless. Therefore, agents in the baseline model have no autonomy – an important characteristic of agents in ABMS.

Agent interaction in the baseline model takes the form of connections between agents on a team. A connection between two agents can be categorized as one of four link types based on the respective states of the agents when the team was constructed. The four types of connections are newcomer-newcomer, newcomer-incumbent, first-time incumbent-incumbent, and repeat incumbent-incumbent (previous collaborators). A network with mostly repeat incumbent-incumbent links may indicate a lack of diverse or innovative ideas in teams (Guimerà et al., 2005) or a set of repeat connections that have been productive in the past, depending on the people involved. Teams with many newcomer-newcomer connections could indicate that experienced workers in the network are not being utilized effectively (Wilensky & Bakshy, 2007). Teams with a variety of connection types combine experience, diverse expertise, and new perspectives, assumed to be a good blend for completing successful projects (Guimerà et al., 2005).

Despite not being an agent-based model, the baseline simulation model illustrates interesting collective behavior based on different parameter settings for agent behavior. The results indicate that the extent to which a team makes involving incumbents a priority has a major influence on the network component structure and thus how connected the network is (Barabási, 2005). Two nodes are part of the same component if starting at one of them and following some number of links eventually leads to the second node. The researchers found that when teams do not maximize incumbents added, the resulting network has many isolated components and very little connectivity among agents (Barabási, 2005). However, when a team increasingly relies on incumbents, the result is an increasingly large single cluster of connected nodes (Barabási, 2005). The results of the baseline model indicate that the best approach to team assembly may be to tend toward including more incumbents, but to avoid always reuniting previous collaborators (Barabási, 2005). That way, experience and expertise are valued and maximized, but diverse perspectives are also incorporated. Teams with this blend of experience and fresh ideas are expected to be the most successful (Barabási, 2005).

A comprehensive description of the adapted model will be presented in Chapter 3 and will explain the similarities and differences between it and the baseline model. The structure of the baseline model is largely preserved in the adapted model, with major changes only in the specific rules for how teams are assembled. As a result, the adapted model considers agents in the same manner as the baseline model. When agents are mentioned in the adapted model description, they are assumed to be included within the context of the relaxed definition of agents used by the creators of the baseline model.

Summary

This chapter provided background on business teams, network theory, an agent perspective, and agent-based modeling and simulation. Employee energy networks and social network analysis were also described since energy is the focus of adapting the baseline model and SNA results inform the motivations behind the strategies and policies modeled. An introduction to the baseline team assembly model that was adapted for the current research was also presented. In Chapter 3, a more detailed description of the baseline model, a description of the adapted model, an explanation of the modeling methodologies for the strategies and policies, and an introduction to the model evaluation framework will be provided.

Chapter 3: Model Description and Methodology

There are two major goals for the simulation model in this thesis: (1) to effectively adapt the baseline team assembly model to include an employee energy component for each agent, and (2) to explore various strategies focused on energy ratings in order to analyze how they affect the average energy of the teams assembled. Energy networks have been explored with network analysis techniques, but little to no research has focused on simulating energy networks. The network simulation model developed in this thesis seeks to demonstrate the value of simulating energy networks and serve as an initial step toward integrating energy networks into an agent-based team assembly model.

For the purposes of the adapted model introduced in this thesis, two strategies are considered for team assembly in a business organization. Teams can either assemble based on similar energy rating or managers can formulate policies for team assembly that place constraints on final team composition. Four different policies will be considered and modeled under this second strategy. This chapter will provide a description of the baseline model, a description of the adapted model, an explanation of the methodology behind the strategies and policies explored, and an introduction to the model evaluation framework.

Baseline Model Description

The baseline model is the NetLogo team assembly model developed by Wilensky (2005), based on research by Guimerà et al. (2005). The baseline model represents a business network of co-worker agents from which project teams of various sizes form. Agents in the model have only a few basic characteristics that influence their behavior: whether they are a newcomer or incumbent and what previous connections they have with other agents if they are incumbents. There are three parameters that can be adjusted to influence behavior in the baseline assembly model: the team size, the probability of choosing an incumbent, and the probability of choosing a previous collaborator.

At each time step of the baseline model simulation, a new team is assembled from incumbents already in the network or newcomers added to it. The two probability parameter values represent various assumptions about the motivations that agents in a team have for adding members to their teams. When the probability of choosing an incumbent is low, team members want to bring new ideas into the team by choosing newcomers. When the probability of choosing an incumbent is high, team members want to make sure that new members have experience and expertise by choosing incumbents. When the probability of choosing a previous collaborator is low, team members want to work with unfamiliar but experienced co-workers. When the probability of choosing a previous collaborator is high, team members want to work with those they have previously worked with. It is possible to change these parameters at each time step, so different teams and team members can have different opinions about the types of agents (newcomers, incumbents, previous collaborators) they prefer to add to their teams. It is also possible to assume that team members across the network will have the same beliefs about adding newcomers and incumbents and leave the parameters unchanged for the duration of a simulation run.

To assemble a team, the model generates a pseudo-random floating-point number and uses the probability of choosing an incumbent to determine if the next team member added will be an incumbent or a newcomer. If the random number generated is greater than the value of the probability of choosing an incumbent, then a newcomer agent is created and added to the team. Otherwise, an incumbent is selected. In this case, the model generates another pseudo-random floating-point number and uses the probability of choosing a previous collaborator to determine if the new team member will be selected from the pool of incumbents who have been on the same team as a current team member or from the pool of any incumbents. In either case, an incumbent is selected at random from one of the two pools of incumbents. Each agent has an identification number (an integer) in the program, so a pseudo-random integer is generated from this pool of incumbents based on a discrete, uniform distribution of the identification values. Agents therefore each have the same probability of being selected equal to one divided by the number of incumbents in the given pool. Incumbents that do not join a team for a certain number of time steps (which can be adjusted) are removed from the network. The randomness present in the model rules is necessary because often there will be a number of agents that meet the requested new team member characteristics, but without additional criteria to factor into the selection decision, one must be chosen randomly.

When a team is constructed in the baseline model, each member is considered connected to the other team members for the duration of their time in the network. Observing the percentages of each of the four link types is a major focus of the baseline model. In addition to keeping track of connection types, the model monitors the overall connectivity of the network by measuring the percentage of agents in the largest cluster of nodes, called the giant component. When nodes from two different components form a link, the two components merge into one and shrink the total number of isolated components in the network. Increasing the size of the giant component causes the network to approach a structure where most nodes can be reached by any other node in the network (Wilensky, 2005a). Often, the connectivity of a network can be characterized by either a single, loosely-connected component or a number of highly-isolated components (Wilensky & Bakshy, 2007). The baseline model indicates that a high probability of choosing incumbents to teams results in a large giant component (high connectivity), while a low probability results in many isolated components (low connectivity). For the adapted thesis model, the focus shifts from overall network connectivity to the effects of various strategies on the average energy of teams.

Adapted Model Description

The simulation model for this thesis is an adaptation of the baseline model. It consists of five distinct models, each with similar structures aside from different rules for team assembly based on an employee energy variable added to the baseline framework. The models integrate each strategy and policy into the rules used to add incumbents to teams. Newly-created agents are given a random, static energy rating stored as a variable value and taken to be an indication of a person's energy level as generally perceived by others. The value of the energy rating determined is selected from a discrete, uniform distribution comprised of the five possible energy levels. The probability of an agent receiving any given energy rating when created is equal to one-fifth. A person's perceived level of energy can affect another person's energy level in a positive, negative, or neutral way (Quinn, 2007). The possibility of a neutral effect indicates that there must be an odd number of units on an energy rating scale to offer a neutral midpoint option. Energy ratings in the adapted model are based on the five-point Likert scale often used in social network analysis surveys. This scale, from one to five, is recoded from zero to four for implementation in the simulation model. Zero represents a strongly de-energizing person, one is a de-energizer, two is neutral, three represents an energizer, and four is a strongly energizing person.

By including an energy rating variable, there are only two parameters that can be adjusted to influence the adapted model: the team size (ranging from four to eight members per team) and the probability of choosing an incumbent. The probability of choosing a prior collaborator is no longer considered, but much of the structure of the baseline model is otherwise preserved in the adapted model. At each time step of an adapted model simulation, a new team is assembled from incumbents already in the network or newcomers added to it. Agents in the model still have only a couple basic characteristics that influence their behavior: whether they are a newcomer or incumbent and their energy rating. Members of the same team are connected and together influence the selection of future members, but a team is not an agent itself. The setting for the probability of choosing an incumbent is a reflection of the motivations that agents in a team have for selecting members for their teams.

In addition to the energy rating variable, a major change to the baseline framework is the introduction of the different strategies and policies for assembling teams. There are five different models, each with an underlying motivation based on real-world scenarios. It is useful to think about the results from each of the five strategy and policy models as if they all came from a single model with five choices for the team members' philosophy for team composition. The different models change the behavior assumptions of team members in terms of who they add to a team, focusing on an agent's energy rating to see if it fits with the current state of the team with regard to the specific model strategy or policy.

The initial state of the network in the adapted model is a connected team of newcomers. At each time step of the simulation, a new team is assembled from some combination of incumbents or newcomers, in the same fashion as in the baseline model. When a team is assembled, the model generates a pseudo-random number and uses the probability of choosing an incumbent to determine if that team member will be an incumbent or a newcomer. If it is a newcomer, a newcomer agent is created (in the same way as in the baseline model), given a random energy rating, and added to the team. If it is an incumbent, the set of rules based on the strategy or policy of the specific model is triggered to find an agent that fits the desired criterion. After an agent has been a member of a team, it resides in the network of available incumbents that can be added to future teams. Agents that do not join a team for a certain number of time steps (which is held constant at 40 times steps for the simulation trials) are removed from the network.

If an agent's characteristics match the criteria that the team is requesting, it will be eligible to join the team. The randomness present in the model rules is necessary because often there will be a number of agents that meet the requested new team member characteristics because only an agent's energy rating is considered as the criterion for selection. Without additional attributes to factor into the selection decision, one must be chosen randomly. A screenshot of the simulation model dashboard and visualization interface can be found in Figure 1.

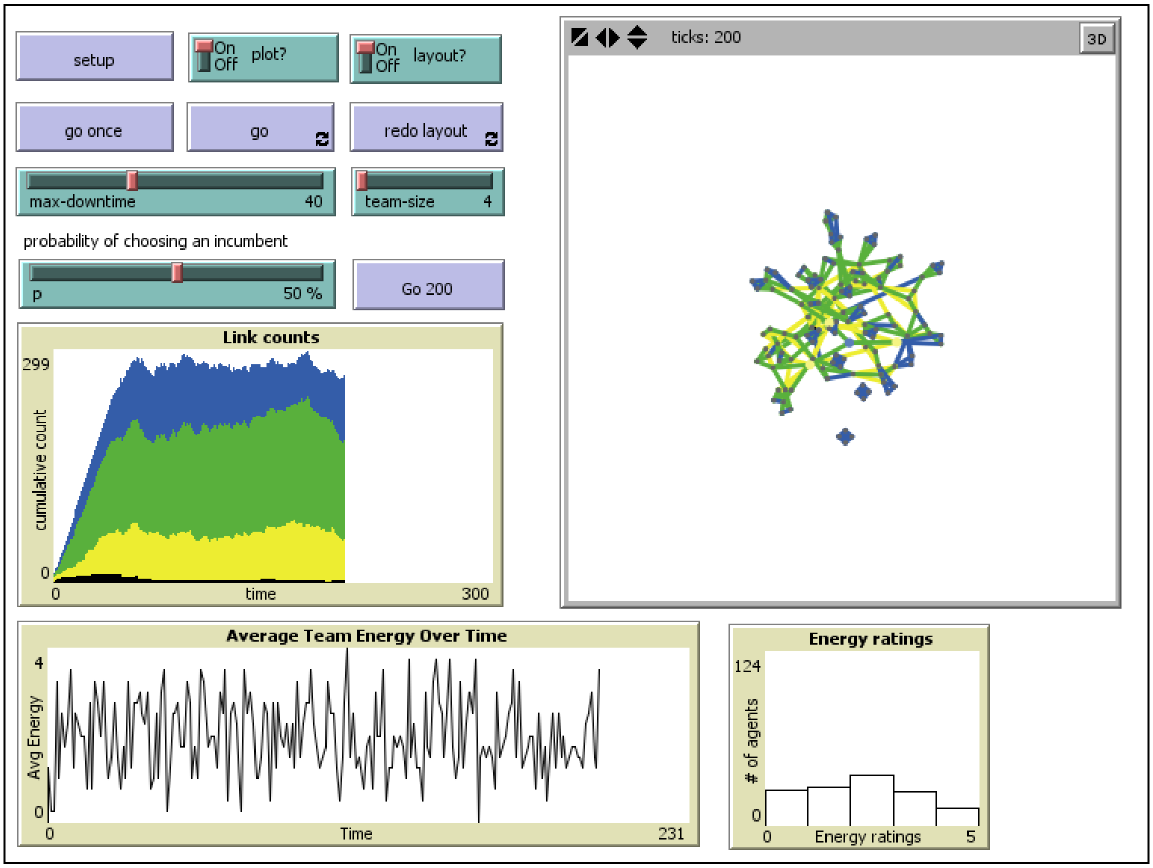

Figure 1: Screenshot of the adapted model dashboard and interface (Strategy 1 model pictured).

Model Strategies and Policies

The strategies and policies modeled in this thesis intend to represent realistic situations that managers could encounter in their organizations. Actual business networks include both energizers and de-energizers, so it is not enough to simulate only team assembly strategies that maximize team energy by always selecting energizing employees. De-energizing employees may not raise the level of enthusiasm of those around them, but they can still contribute to an organization in other positive ways. Therefore, a realistic model of business team assembly must include scenarios that include de-energizers. The motivation of the model is to understand how the different assumptions about integrating energizers and de-energizers affect the average energy of teams. The adapted simulation model considers two strategies for team assembly in business organizations:

1. Team assembly based on similar energy ratings.
2. Team assembly with respect to team composition constraints.

For the first strategy, it is assumed that agents will form teams with other agents that have similar energy ratings. The motivation for this strategy is that in the real world people tend to want to work with others they feel comfortable with (Cross et al., 2008). The assumption in this adapted model is that workers will be comfortable working with, and thus will want to work with people with similar energy ratings. This strategy, therefore, operates under the framework of preferential attachment with fitness, where fitness is represented by similar energy rating. The concept of preferential attachment states that nodes prefer to link to the most popular nodes in a network, that is, the ones with the highest degree or number of connections with other nodes (Wilensky, 2005b). While preferential attachment based on degree is the most common example, any criterion can be substituted in place of degree to favor one link over another. Preferential attachment with fitness works in this way by basing the connection decision on some intrinsic quality of the node (Borgs, Chayes, Daskalakis, & Roch, 2007). In this model, each agent node has an inherent energy rating that acts as a proxy for quality in the preferential attachment with fitness framework.

Allowing team assembly based on similar qualities can be productive, but it does not always lead to the most effective teams in an organization (Cross et al., 2008). There may be less diversity in the workers added to a team, and additionally, this method might not maximize the skills of people in the network. In some cases, managers need to implement policies that constrain team composition in some way. The second strategy operates under this framework based on the idea that it can be beneficial to strategically place employees with certain characteristics in teams throughout an organization to distribute their influence and hopefully increase productivity as a result (Cross et al., 2008). In this case, the strategy focuses on different ways of spreading energizers and de-energizers throughout teams to observe how it affects team energy. Teams are assembled with respect to the individual variables of worker agents based on the external regulations that the various strategies and policies require.

A number of different requirements could be implemented for this strategy, so four different policies will be considered and modeled for the second strategy in this model:

2a. Managers want to balance the energy level of teams by including both energizing and de-energizing employees.

2b. Managers want teams to include at least one de-energizing team member, but otherwise want energizing workers.

2c. Managers want teams with mostly de-energizers to include at least one energizing worker to raise the average energy of the team.

2d. Managers want a high level of variability in the energy ratings of team members, so at least one team member with each energy rating must be present in a team before incumbents with repeat energy ratings can be added to a team.

For each strategy and policy, the team assembly rules and team composition constraints apply only to incumbents in the network. Newcomers are added to teams without adhering to any constraints put in place by the strategies or policies. This is an assumption based on the real-world situation that workers often do not know about the energy of newcomers since it takes some time and some number of interactions to build an energy perception. As a result, in the adapted model newcomers are not evaluated based on energy prior to joining a team. Whenever a newcomer is selected to join a team, one is created and added regardless of energy rating.

There are two major limitations of the adapted model. The first is the assumption that teams are assembled based entirely on a single factor: a worker's energy rating. In actual organizations, a number of different characteristics, skills, and competencies are considered when assembling teams. This simplifying assumption is acceptable for this study because the intention of the adapted model is to focus on energy in a network simulation model to investigate how different assembly strategies would affect average team energy.

The second major limitation is that an agent's energy rating in the model represents its level of energy as perceived by others, but the way it is integrated, every agent has the same perception of a given agent. This perception is actually subjective in the real world, varying from person to person. Furthermore, agents have the same energy rating throughout the entire simulation which is not consistent with the real world because energy is not a static or permanent characteristic of each person, but rather a dynamic perception that is constantly changing based on how others view that person's energy level in interactions. A worker's perception of a co-worker's energy will often evolve over time. A model that most accurately represents energy networks in an organization would have to update an agent's energy after each team formation as a way to represent changes in energy perception that occur after interactions with others. Since the adapted model seeks only to analyze strategies for team assembly and the effect on average team energy, it is enough to simply include a static energy component to each agent's characteristics. A permanent energy rating is a reasonable assumption for a short-term model, and including this variable effectively frames the strategy and policy rules implemented and the behavior observed within the context of energy networks, facilitating the goal of the thesis model.

Modeling Methodology

For each of the five strategy and policy models, the overall model structure is the same except for the specific rules for adding incumbents to a team. In order to better understand how each strategy and policy is programmed, a detailed breakdown of the methodology behind each is outlined.

Strategy 1:

For the first strategy, teams assemble based on preferential attachment with fitness, where fitness is considered an energy rating that is most similar to the team's average energy. The assumption is that agents will want to join teams with other agents of similar energy and the current members of a team will want to add agents with similar energy to their own. Initially, a pseudo-random integer between zero and four (discrete uniformly distributed) is generated by the simulation program and assigned to the average team energy variable until the first member is added to the team. If a newcomer is the first agent added to the team, the team's average energy then becomes based on that newcomer's energy rating. If an incumbent is the first agent added to the team, that incumbent is chosen based on the initial random team energy average. The team's average energy then becomes based on the first team member's energy rating. When subsequent incumbents are added, they are chosen from the pool of agents with energy ratings within plus or minus one of the current average team energy if any incumbents that are from within that range and not already on the team exist (meaning they are available). Otherwise, any available incumbents are added to the team.

Strategy 2:

For the second strategy, teams assemble with respect to certain constraints put in place regarding team composition. The following four policies are investigated:

Policy 2a:

The assumption for this policy is that managers want to balance the energy level of teams by including both energizing and de-energizing employees. On the energy rating scale, two is the midpoint and represents neutral energy in the model. As long as the average team energy is greater than two, only incumbents with an energy rating less than two are added. As long as the average team energy is less than two, only incumbents with an energy rating greater than two are added. As long as the average team energy is exactly two, only incumbents with an energy rating equal to two are added in order to maintain the current neutral team energy level. If no incumbents with the preferred energy ratings are available in the first two cases, an available incumbent with an energy rating equal to two will be chosen. If there are no incumbents with the preferred energy ratings and no incumbents with an energy rating of two available, any available incumbent will be chosen.

Policy 2b:

The assumption for this policy is that managers want teams to include at least one team member with an energy rating less than two, but otherwise want energizing workers. The motivation is to include de-energizers in teams, but limit their negative impact by putting them with mostly energizers. When a team has no member with an energy rating less than two, an incumbent with an energy rating less than two will be chosen if available. If one is not available, then an incumbent with an energy rating greater than two will be chosen if available. If an incumbent with an energy rating greater than two is not available, an incumbent with an energy rating equal to two will be chosen if available. When a team already has a member with an energy rating less than two, an incumbent with an energy rating greater than two will be chosen if available. If an incumbent with an energy rating greater than two is not available, an incumbent with an energy rating equal to two will be chosen if available. If an incumbent with an energy rating equal to two is not available, any available incumbent will be chosen.

Policy 2c:

The assumption for this policy is essentially the converse of Policy 2b: managers want teams with mostly de-energizers to include at least one energizing worker to raise the average energy of the team. The final composition of these teams should therefore have mostly members with de-energizing ratings, but at least one with an energizing rating. If a team has no team member with an energy rating greater than two, an incumbent with an energy rating greater than two will be chosen if available. If one is not available, then an incumbent with an energy rating less than two will be chosen if available. If an incumbent with an energy rating less than two is not available, then an incumbent with an energy rating equal to two will be chosen if available. When a team already has a member with an energy rating greater than two, an incumbent with an energy rating less than two will be chosen if available. If an incumbent with an energy rating less than two is not available, an incumbent with an energy rating equal to two will be chosen if available. If an incumbent with energy equal to two is not available, any available incumbent will be chosen.

Policy 2d:

The assumption for this policy is that managers want a high level of variability in the energy ratings of team members, so incumbents can join a team only if their energy rating is not the same as the energy rating of a worker already on the team or if there is already a team member with each energy rating present. For team sizes greater than five (since there are five units on the energy rating scale), incumbents with repeat energy ratings can be added after each of the other energy ratings are represented on a team. Once team members with each of the five energy ratings are present on a team, incumbents with any energy rating can be chosen and added to the team. While this does allow for an energy rating to repeat more than once in some cases, the chances of this happening are low. Assuming that teams have all incumbent members (which often doesn't occur because the probabilities of choosing an incumbent used in simulation trials allow for newcomers to be added to a team), the chances of having the same energy rating present three times is equal to 4% and the chances of having the same energy rating present four times is less than 1%. The model keeps track of the energy ratings of agents currently on a team in an array. When it is determined that an incumbent will be added to a team, one is randomly chosen from available workers who have an energy rating not listed in that array.

Model Evaluation

The strategies and policies modeled intend to address realistic situations that managers could encounter in their business organizations. The motivation of this simulation model is to understand how the different assumptions made in the strategies and policies affect average team energy. The intent is not to determine the best strategy for optimizing a specific objective function related to average team energy. Rather, the analysis of this model is better-suited for and aimed at comparing how the different strategies and policies impact average team energy and drawing conclusions about them based on the model results.

If the intent of this study were to maximize the average team energy, it would be easily done by setting the rules to always add available agents in the network with the highest energy ratings. Teams would still have some variability because of newcomers, but overall this methodology would maximize team energy. This scenario is not very realistic, however. One of the reasons that analyzing energy networks is useful is that both energizers and de-energizers comprise organizations and must be integrated into project teams. While de-energizing employees do not facilitate enthusiasm in others, they can still be valuable or even integral contributors to an organization. Therefore, the strategies and policies modeled seek to address realistic scenarios in which teams must be comprised of both energizing and de-energizing workers.

Summary

This chapter provided descriptions of the baseline and adapted models, an explanation of the modeling methodology for the strategies and policies explored, and an introduction to the model evaluation framework. The goals for the simulation model in this thesis are to integrate an employee energy component into the baseline model and to explore various strategies focused on energy ratings in order to analyze how they affect average team energy over time. Chapter 4 will present the verification and validation process and the specific techniques utilized to test the adapted model.

Chapter 4: Model Verification and Validation

Verification and validation assess and establish the credibility of a simulation model. Verification is the process of ensuring that a model does what it is programmed to do (Gilbert, 2008). Verification is often called debugging and usually involves some systematic procedure for thoroughly testing program code in various scenarios to make sure there are no compilation or runtime errors. Once a model has been verified, it must be validated (Gilbert, 2008). Validation is the process of determining whether a model is an accurate depiction of the system being modeled (Gilbert, 2008). Simulation modeling is done when it is inconvenient, inefficient, or impossible to experiment directly on a target system (Law, 2008). A simulation model can never completely replicate a real-world system, but is meant to represent the target system as closely as possible to provide accurate results (Law, 2008). A simulation model can never be completely verified or validated, it can only pass all verification and validation tests (Macal & North, 2007). After thorough testing, a simulation model can be considered suitable to provide credible and usable results.

This chapter presents and describes the specific verification and validation techniques used to test the simulation model in this study. Verification methods used include logical test cases and extreme value tests. Each strategy or policy for adding agents to a team is based on some underlying motivation that differs in each of the models. Logical test cases ensure that the rules that have been coded for each model match these motivations and work as programmed in multiple scenarios. Model behavior can often be predicted for maximum and minimum variables so extreme value tests are used to ensure that the model arrives at anticipated results in such cases. Validation methods used include face validity, results validation, objectives validation, and sensitivity analysis. Face validity checks if a simulation model appears consistent with the way the target system is perceived to operate (Law, 2008). Results validation compares the model results to observed behavior and output data from the actual system, and objectives validation confirms that a model meets the purposes or goals specified for building the model (Law, 2008). Sensitivity analysis aims to illustrate what conditions cause expected results, how sensitive outcomes are to changes in initial conditions, and which factors have a major influence on results (Gilbert, 2008; Law, 2008).

Model Verification

The initial verification steps involved repeatedly running the simulation for about 20 time steps to make sure that the program code compiled and the simulation initially ran with no errors. One of the specific aspects of verifying this model was ensuring that the program code for adding agents to teams contained rules for addressing every possible situation as far as the availability of agents in the network. Most of the strategy and policy variations involve nested if-else decision rules that need to be complete in order for full teams to be assembled and for the model to run entirely. Errors that occurred early in runs often meant that a rule was missing for adding agents when none of the criteria being used for that specific strategy was triggered. For example, in a case where the model rules call for a team to add an agent with an energy rating equal to three, if there are no agents with that energy rating available in the network, then there must be a rule to choose an agent based on different criteria or to choose any available agent. Otherwise, the model will stop and display a runtime error because the program has no instructions for how to complete the task of adding an agent in that situation. This verification technique was a useful way to ensure that the code, especially the if-else statements, was completely specified.

Because there is randomness in the team assembly process, it was possible for a model with incomplete decision rules to run without error on a given replication. Each of the strategies and policies represented in the model determine which agents are going to be added to the current team based on energy ratings. The model could neglect to insert a rule that says to choose any available agent in the network if there is not one that meets the current selection criteria. Since the agents in a network and their energy ratings are determined randomly, it is possible for this model to run without error if it encounters a specific combination of agents and energy ratings in a given replication. As an example, assume that the initial team assembled for a set of simulation runs had four team members with energy ratings of one, two, three, and four, respectively. If, in the second time step, the model rules called for a team with two newcomers and two incumbents with energy ratings of two, the model would not be able to complete its run if there is no instruction for what to do when there is not an available agent that meets the requested criteria. However, a model without that extra instruction would still be able to assemble a team with two newcomers and incumbents with energy ratings of two and four, respectively. The results are based entirely on the incumbents available in the network. As a result, repeatedly running the simulation to check for initial runtime errors was often the only way to notice problems in the program code. If the simulation was tested only once, it would have been possible for the model to run without error that one time despite actually having problems in the rules.

The initial attempt to integrate an energy component into the baseline model was based on the notion that each team would prefer its members to have some minimum or threshold energy rating. For example, if an energy rating threshold of three was chosen, teams would prefer to add team members with energy ratings greater than or equal to three. If there were no available agents above that threshold, any available agent would be selected. To verify whether the threshold model worked as expected, one would need to ensure that incumbent agents with appropriate energy ratings (when available) are always added to the team ahead of other agents. NetLogo has an “inspect” feature that allows the modeler to select any agent in a model and see all of its variable values and traits. By inspecting the agents that were part of the current team, it could be determined whether they had the appropriate energy ratings based on the rules in the model. This threshold methodology was not used in any of the final models analyzed, but the process of verifying it led to a method for manually examining the energy ratings of current team members after each time step to verify that the model code was correct.

Once the strategies and policies for the models were determined, it became apparent that an additional verification step was needed. In the models, the rules that determine what the energy rating of an agent to be added to a team can or will be are influenced by the average energy rating of the current team or the specific energy ratings of the current team members. Therefore, it is important to record the order that agents are added to a team when verifying each of the models. A complication for this specific model is that result of each time step is a fully-assembled team with no indication of the order in which the agents were added. To keep track of the order in which agents are added to a team, an order-tag variable was created and updated throughout the process of team assembly. Checking the order-tags of team members after each time step reveals whether agents with appropriate energy ratings were added to a team based on the agents that were already on the team.

Using the inspect feature in NetLogo and the order-tag variable created, the different strategy and policy models were verified. Initial tests were not standardized; an assorted number of time steps were analyzed, the point in time where a simulation was tested varied, and different information was recorded about each assembled team. A few code issues were found during this initial verification. There was a runtime error in the first strategy model that occurred infrequently when trying to run the simulation repeatedly. A problem with the if-else statements was also discovered and corrected by simplifying the program code. In the second policy model, activity inconsistent with the decision rules was discovered after inspecting the first set of team members, and the agent rules were reprogrammed. This unsystematic verification process led to a more uniform procedure for verifying the models and recording the various important factors.

To verify the model, the following framework was used for each strategy or policy simulation:

- Verify ten time steps beginning at time step 101 with a probability of choosing an incumbent equal to 25%.
- Verify ten time steps beginning at time step 101 with a probability of choosing an incumbent equal to 50%.
- Verify ten time steps beginning at time step 101 with probability of choosing an incumbent equal to 95% after running simulation for 100 time steps with probability of choosing an incumbent equal to 50%.

When the probability of choosing an incumbent is set to 25% and 50%, a mix of newcomers and incumbents are added to teams. These two methods focus on ensuring that the rules for choosing incumbents work as programmed when newcomers are regularly added to teams. For the third verification method, the model initially set the probability of choosing an incumbent at 50% for 100 time steps to populate the network with agents, and then changed it to 95% so that mostly incumbents were added to teams for the ten time steps that were examined. The strategies and policies in the model apply only to incumbents, so this method makes it easier to ensure that the rules are programmed correctly since very few newcomers are added.

For each strategy and policy simulation, the verification test recorded the arrival of each agent in order, its energy rating, and whether it was an incumbent or newcomer. There were four sets of additional information that needed to be recorded for specific strategies or policies.

Set 1: the average energy of the team after each agent was added.

Set 2: whether or not an agent with an energy rating less than two was currently a member of the team after each agent was added.

Set 3: whether or not an agent with an energy rating greater than two was currently a member of the team after each agent was added.

Set 4: whether there were any repeat energy ratings in the team (as a result of newcomer energy ratings or a team size greater than five).

Explaining specifically how each strategy and policy was verified will illustrate further the logical test case verification process.

For the first strategy, agents are added to a team based on similar energy rating. After each agent is added to a team, the average energy of the team is updated so that the next agent added – if an incumbent – will have an energy rating within a range of plus or minus one from the average energy of the team. The basic observation that must hold for this strategy to be simulated correctly is that an incumbent with an energy rating that falls within the determined range must be added to the team if one is available. When a newcomer is added to a team, its energy rating does not have to fall in the range. The average energy of the team was determined after each agent was added to the team to ensure that incumbents added to the team had energy ratings that fell within the required range as determined by the team's average energy at that point in time. The three verification tests were run with four-person teams to verify the first strategy model and recording set one was used.

For the second strategy, there are four policies and each has a different constraint for the teams that are being assembled. Policy 2a assumes that managers want teams to balance the energy level of teams by including both energizing and de-energizing employees. There were three basic observations that must hold for this policy to be simulated correctly. If the average team energy rating is greater than two, the next incumbent added should have an energy rating less than two. If the average team energy rating is less than two, the next incumbent added should have an energy rating greater than two. If the average team energy rating is equal to two, the next incumbent added should have an energy rating equal to two. The team members were inspected after each time step to ensure that the incumbents that were added had energy ratings that fell within the required range as determined by the current team's average energy. The three verification tests were run with four-person teams to verify the Policy 2a model and recording set one was used.

Policy 2b assumes that managers want teams to include at least one team member with an energy rating less than two, but otherwise want energizing workers. The basic observation that must hold for this policy to be simulated correctly is that if there is not currently a team member with an energy rating less than two, then the next incumbent to be added to the team must have an energy rating less than two. The team members were inspected after each time step to ensure that the first incumbent added to the team had an energy rating less than two if there was no current team member with an energy rating less than two already present on the team. The three verification tests were run with four-person teams to verify the Policy 2b model and recording set two was used.

Policy 2c assumes that managers want teams with mostly de-energizers to include at least one energizing worker to raise the average energy of the team. The basic observation that must hold for this policy to be simulated correctly is that if there is not currently a team member with an energy rating greater than two, then the next incumbent to be added to the team must have an energy rating greater than two. The team members were inspected after each time step to ensure that the first incumbent added to the team had an energy rating greater than two if there was no current team member with an energy rating greater than two already present on the team. The three verification tests were run with four-person teams to verify the Policy 2c model and recording set three was used.

Policy 2d assumes that managers want a high level of variability in the energy ratings of team members, so incumbents join a team only if their energy rating is not the same as the energy rating of a worker already on the team. The basic observation that must hold for this policy to be simulated correctly is that a team member with an energy rating already present on the team cannot be added until each of the other energy ratings is also present. With larger team sizes, incumbents with repeat energy ratings can be added only after each of the five energy ratings is represented. The team members were inspected after each time step to ensure that incumbents with repeat energy ratings were added to the team only after team members with each of the other energy ratings were present. The three verification tests were run with four-person and eight-person teams to verify the Policy 2d model and recording set four was used.

Extreme value tests were also conducted for each of the strategy and policy models to ensure that when the probability of choosing an incumbent was 0% or 100%, the resulting behavior was as expected. When the probability of choosing an incumbent is set to 0%, assembled teams are always comprised of newcomers who never join another team while in the network and eventually leave the network after the specified duration of inactivity. When the probability of choosing an incumbent is set to 100%, the newcomers who comprised the initial team repeat as incumbent team members for every time step of the current simulation run. The expected behavior was observed for each of the extreme values.

Once the model was verified thoroughly for the tests outlined, it could be used to run some initial simulations for validation to ensure that it produced credible results and met the intentions outlined for its use.

Model Validation

The first validation technique used was face validity, which checks if a simulation model appears consistent with the way the target system is perceived to operate (Law, 2008). There is no specific system with which to compare the team assembly simulation in this thesis. However, it is an adaptation of the baseline model and does not alter the overall structure of that model, only the specific rules for how team members are added to a team. Therefore, if the baseline model is considered valid and credible – and it is assumed to be since it is featured in the NetLogo sample model library – then likewise the adapted model should be considered valid and credible.

Furthermore, the assumptions used to form the rules programmed for the various strategies and policies are all rooted in observed behavior in real-world organizations and reported in the literature. The observed tendency of employees to work with people similar to them or that they feel comfortable with directly influences the Strategy 1 model. The concept of spreading a specific competency throughout teams in a network informs the various policy models for the second strategy. Additionally, the energy scale used to classify the energy rating of each agent is based on published literature about the network analysis surveys used to collect relationship data in actual organizations.

Since the simulation model is not based on an existing team assembly system, there is no empirical data for comparison and results validation. However, for a few of the strategy and policy models, some general expected simulation results could be inferred prior to the simulation based on the implemented rules and used as a less strict form of results validation. Policy 2b is designed to produce teams with mostly energizing members, but at least one de-energizing member. Therefore, it would be expected that the average team energy results for this model would usually be greater than two, the neutral midpoint energy level. With newcomers not impacted by the team composition restrictions and able to be added to teams, average team energy will not always be energizing for Policy 2b. However, observing energizing team ratings the majority of the time – especially when the probability of choosing an incumbent is greater than 50% – is a good indication that the results of this model are valid. The Policy 2c model presents a similar situation. The policy is designed to produce teams with mostly de-energizing members, but at least one energizing member in an attempt to raise the average energy of the team. Therefore, it would be expected that the average team energy results for this model would usually be less than two especially as the probability of choosing an incumbent increases. In each of these cases, only very general expectations about the model results can be made and there is no way to predict the exact behavior (if there was, it would not be necessary to build and run the simulation model) (Law, 2008).

Since a simulation model is developed to meet an objective or set of objectives, another validation method is to ensure that the model achieves the purpose for building it. The intentions for the simulation model in this thesis are to integrate an employee energy component into the baseline model and to explore various strategies focused on individual energy ratings. The adapted model accomplishes these objectives.

Sensitivity analysis aims to illustrate what conditions cause expected results, how sensitive outcomes are to changes in initial conditions, and which factors have a major influence on results (Gilbert, 2008; Law, 2008). Based on the motivations and assumptions that influence each of the strategies and policies, there seemed to be a partition between those that would balance out average team energy at the neutral value of two and those that would not. Strategy 1, Policy 2a, and Policy 2d appeared likely to achieve average team energy over time of approximately two. Policy 2b places at least one de-energizing employee in otherwise energizing teams and Policy 2c places at least one energizing employee in otherwise de-energizing teams, so these two policies would likely not have average team energy (or simply team energy) around two. Sensitivity tests were run for one model from each of these two groups – Strategy 1 and Policy 2b – to see how various probabilities of choosing an incumbent affected the mean and standard deviation of team energy for the extreme team sizes (four and eight). Five probabilities of choosing an incumbent were examined: 10%, 25%, 50%, 75%, and 90%. The probabilities of 25%, 50%, and 75% were used in the simulation trials (to be explained in Chapter 5) to provide a model results for analysis. The probabilities of 10% and 90% were included to analyze sensitivity at values closer to the extremes. Since there is randomness in the adapted models, multiple replications were needed to give an adequate sample of data. Five sample replications of the simulation were run for each of the ten parameter combinations for both of the models with results shown in Tables 1 through 4.

Table 1: Sensitivity Analysis Data Set 1: Team Energy for Strategy 1 with Team Size of Four.

Strategy 1 with Team Size of Four					
	Probability of Choosing an Incumbent				
	10%	25%	50%	75%	90%
Mean	1.98	1.97	1.97	1.97	2.11
Standard Deviation	0.75	0.78	0.91	1.04	1.05

Table 2: Sensitivity Analysis Data Set 2: Team Energy for Strategy 1 with Team Size of Eight.

Strategy 1 with Team Size of Eight					
	Probability of Choosing an Incumbent				
	10%	25%	50%	75%	90%
Mean	1.98	2.05	2.00	2.02	1.94
Standard Deviation	0.49	0.56	0.76	0.98	1.01

Table 3: Sensitivity Analysis Data Set 3: Team Energy for Policy 2b with Team Size of Four.

Policy 2b with Team Size of Four					
	Probability of Choosing an Incumbent				
	10%	25%	50%	75%	90%
Mean	2.04	2.02	2.21	2.51	2.57
Standard Deviation	0.70	0.59	0.58	0.47	0.44

Table 4: Sensitivity Analysis Data Set 4: Team Energy for Policy 2b with Team Size of Eight.

Policy 2b with Team Size of Eight					
	Probability of Choosing an Incumbent				
	10%	25%	50%	75%	90%
Mean	2.11	2.18	2.45	2.75	2.92
Standard Deviation	0.50	0.42	0.43	0.37	0.42

For Strategy 1, for both team sizes tested, the means remain very close to two as expected, but the standard deviations vary. Standard deviation ranges from 0.75 to 1.05 for the smaller team size of four (Table 1) and from 0.49 to 1.01 for team size of eight (Table 2). In both cases, the standard deviation increases as the probability of choosing an incumbent increases. For Policy 2b, the standard deviations of team energy (Tables 3 and 4) are more narrowly distributed than those of Strategy 1 (Tables 1 and 2), while the means are more varied. The means of team energy across the five different probabilities are all greater than two (Tables 3 and 4) and are more widely distributed than the means of team energy for Strategy 1 (Tables 1 and 2). In most cases, the values of team energy for Policy 2b increase as the probability of choosing an incumbent increases. In order to check the significance of this sensitivity data, difference of means tests were performed.

Two-sample t-tests assuming unequal variances were conducted to compare the differences of means between 10% and 25% probability of choosing an incumbent and 75% and 90% probability of choosing an incumbent for each of the data sets. The level of significance used was $\alpha = 0.05$ and the null hypothesis was equal means. Each difference of means test determined a p-value (Tables 5 and 6). If the p-value for a given set is less than $\alpha = 0.05$, the null hypothesis of equal means is not rejected.

Table 5: Strategy 1 p-values determined from difference of means tests.

Strategy 1 P-Values			
Team Size of Four		Team Size of Eight	
Difference between 10% and 25%	Difference between 75% and 90%	Difference between 10% and 25%	Difference between 75% and 90%
p-value = 0.85	p-value = 0.12	p-value = 0.11	p-value = 0.34

Table 6: Policy 2b p-values determined from difference of means tests.

Policy 2b P-Values			
Team Size of Four		Team Size of Eight	
Difference between 10% and 25%	Difference between 75% and 90%	Difference between 10% and 25%	Difference between 75% and 90%
p-value = 0.80	p-value = 0.19	p-value = 0.09	p-value = 2.02E-06

For Strategy 1 with team sizes of both four and eight, the difference of means tests confirm that the null hypothesis of equal means cannot be rejected for the means at 10% and 25%, as well as the means for 75% and 90%. For Policy 2b with team size of four, the difference of means tests confirm that the null hypothesis of equal means cannot be rejected for the means at 10% and 25%, as well as the means for 75% and 90%. For Policy 2b with team size of eight, the difference of means tests confirm that the null hypothesis of equal means cannot be rejected for the means at 10% and 25%, but can be rejected for 75% and 90%, so we can conclude that the means differ. Since we cannot conclude that the means are different for every case of comparing 10% and 25% probability of choosing an incumbent and all but one case of comparing 75% and 90% probability of choosing an incumbent, this analysis suggests that the model evaluation framework that focuses on probabilities of choosing an incumbent of 25%, 50%, and

75% is adequate and the model is not sensitive to the extreme values of probabilities of choosing an incumbent.

Once the model passed the validation methods outlined, it could be taken as credible in terms of meeting the intentions for its use and producing results that are consistent with observations made about real-world business team assembly.

Summary

This chapter described the verification and validation process and emphasized the importance of testing the simulation model. The specific techniques utilized to verify and validate the adapted models in this study were presented in an effort to build credibility in the simulation results obtained from them. The adapted models passed all verification tests, ensuring that the strategy and policy rules for adding incumbents were programmed correctly and that expected results were produced when extreme values were used in the model. The adapted models also passed all validation tests, ensuring that model structure and behavior were consistent with the valid baseline team assembly model, scenarios with expected results were confirmed, and model objectives were met. As a result, the adapted simulation model is taken to be credible and usable. Chapter 5 will provide a description of the simulation trials conducted and a description of the results.

Chapter 5: Model Results

This chapter presents an explanation of the model simulation trials conducted and a description of the results. Simulation trials were run for the various combinations of the model parameters: team size and the probability of choosing an incumbent. The results focus on the average team energy and include three major data sets: mean of team energy, the frequency of occurrence of energizing teams, and the frequency of occurrence of de-energizing teams.

Model Simulation Trials

Each of the adapted model variations was simulated to provide trial data for exploring the many different combinations of parameter values. Two parameters were adjusted in the five models – the team size and the probability of choosing an incumbent – resulting in 500 different variable combinations. To limit the model testing to a more practical level, only a selection of these combinations were run for analysis. There are five different team sizes (four to eight) possible in the model and each was considered in the simulation trials. Three probabilities of choosing an incumbent were considered (25%, 50%, and 75%) to give varying chances of adding incumbents and newcomers to teams. For each of the five strategy and policy models, there are 15 different combinations tested resulting in a total of 75 different model combinations simulated.

The average energy of the team assembled at each time step was recorded and plotted for 200 time steps per simulation replication. Since each time step in the simulation produces a discrete assembled team, it does not take long for the simulation to reach a steady state. The only impact a prior step's team has on the next team assembled is possibly adding more agents to the pool of available incumbents in the network. By the time the pool of available incumbents has at least as many agents of each energy rating as the team size for the particular model, any requested team composition can be facilitated and the model reaches a steady state. Incumbents were removed from the network after 40 time steps of not joining a team, which was held constant across models.

Since the simulations involve randomness, multiple replications of runs were needed to illustrate the amount of variability in the results. A formula for determining the optimal number of replications based on achieving a specific error level at a selected confidence interval was used (Harrell, Ghosh, & Bowden, 2000). The formula is as follows, with $Z_{\alpha/2}$ = a value from the standard normal distribution based on the desired significance level, s = standard deviation from a sample set of data, and e = desired confidence interval half-width:

$$\left[\frac{Z_{\alpha/2} \cdot s}{e}\right]^2 \tag{1}$$

The formula is based on sample data from the model so each of the five strategy and policy models was run ten times for 200 time steps for each of the combinations of team sizes and probabilities of choosing an incumbent. The mean and standard deviation of average team energy were calculated for each model combination across the ten replications. Usually the optimal number of replications formula is applied to a single model with one mean and one standard deviation as a result of the sample replications. However, since there are so many combinations of model parameters in this case, the largest standard deviation obtained from the sample runs was used for the formula. Using the largest standard deviation establishes a wider confidence interval, but ensures that all of the other combinations will be included within that interval (since each has less variability than the one chosen).

The Strategy 1 model with a team size of four and a probability of choosing an incumbent of 75% produced the largest standard deviation, 1.03, with an associated mean of 1.99. The confidence interval selected was 95%, which determines a Z-value of 1.96 from the standard normal distribution for that significance level. The acceptable half-width selected was 0.4 (or about 20% of the mean of 1.99). These values were used in the formula as follows to determine an optimal number replications equal to 25.4 replications, which was rounded up to 26 to include the fraction of a replication:

$$\left[\frac{1.96 \cdot 1.03}{0.4}\right]^2 = 25.4 \approx 26 \text{ replications} \quad (2)$$

The acceptable half-width determines the size of the confidence interval. A half-width equal to 20% of the sample mean is reasonable because the purpose of the models in this study is to explore realistic strategies and policies for assembling teams based on energy rating. In a study with the intent of optimizing an objective function related to average team energy to determine the best strategy, it would make more sense to have a lower acceptable error in order to minimize the risk of making a poor choice. In this explorative simulation model, there is minimal risk so a larger acceptable error is reasonable. For each of the parameter combinations, 26 replications were conducted.

Model Results

At each time step of the simulation for the adapted model, a team is assembled. The average energy of the team is calculated by summing the energy ratings of each team member and dividing by the team size. Average team energy was calculated for each of the 75 model combinations for 26 replications and aggregated to determine a single set of average team energies for each combination. For the purposes of the model results and analysis, average team energy is referred to as team energy (or team energy rating) from this point forward.

Three major sets of data are presented to demonstrate the effects of the various strategies and policies on team energy. The mean of team energy is calculated for each combination to illustrate what team energy tends to be over a large number of replications. The standard deviation of the mean of team energy is also included with this first data set to assess the level of variability. These two statistics do not provide a complete picture of the model results, however. It is also important for managers to determine how often energizing and de-energizing teams result. The other two data sets collected, therefore, are the frequency of occurrence of energizing teams and the frequency of occurrence of de-energizing teams. An energizing team is defined as having a team energy rating greater than or equal to three. A de-energizing team is defined as having a team energy rating less than or equal to one. The frequencies of occurrence of energizing and de-energizing teams are determined by dividing the number of instances of energizing and de-energizing teams for each strategy or policy by the total number of teams assembled, 5200 (26 replications times 200 time steps).

Mean of Team Energy

The mean of team energy for each combination of strategy or policy, team size, and probability of choosing an incumbent for 26 replications is graphed in Figures 2 through 4. Confidence intervals of 95% were also calculated based on the standard deviations of each data set and added to Figures 2 through 4 to indicate where the means overlap across team sizes for each strategy or policy. In addition to the mean of team energy graphs, the corresponding standard deviations of these means are presented in

Tables 7 through 10. Strategy 1, Policy 2a, and Policy 2d all have mean team energy close to the neutral level of two over the 26 replications, regardless of the team size or probability of choosing an incumbent. For these three strategies and policies, the confidence intervals overlap for the team energy for each team size so it cannot be concluded with 95% confidence that the means are different.

Policy 2b has mean of team energy slightly greater than two at a 25% probability of choosing an incumbent (Figure 2), increased team energy at 50% (Figure 3), and further increased team energy at 75% (Figure 4). By 75% probability, almost all team sizes have team energy greater than or equal to 2.5. The amount greater than two for the mean of team energy increases slightly as the team size increases from four to eight. Policy 2c has team energy slightly less than two at a 25% probability of choosing an incumbent (Figure 2), decreased team energy at 50% (Figure 3), and further decreased team energy at 75% (Figure 4). By 75% probability, almost all team sizes have team energy less than or equal to 1.5. The amount less than two for the mean of team energy decreases slightly as the team size increases from four to eight. The confidence intervals do not overlap for the team energy means for each team size for Policy 2b and Policy 2c, meaning that it can be stated with 95% confidence that the means are different.

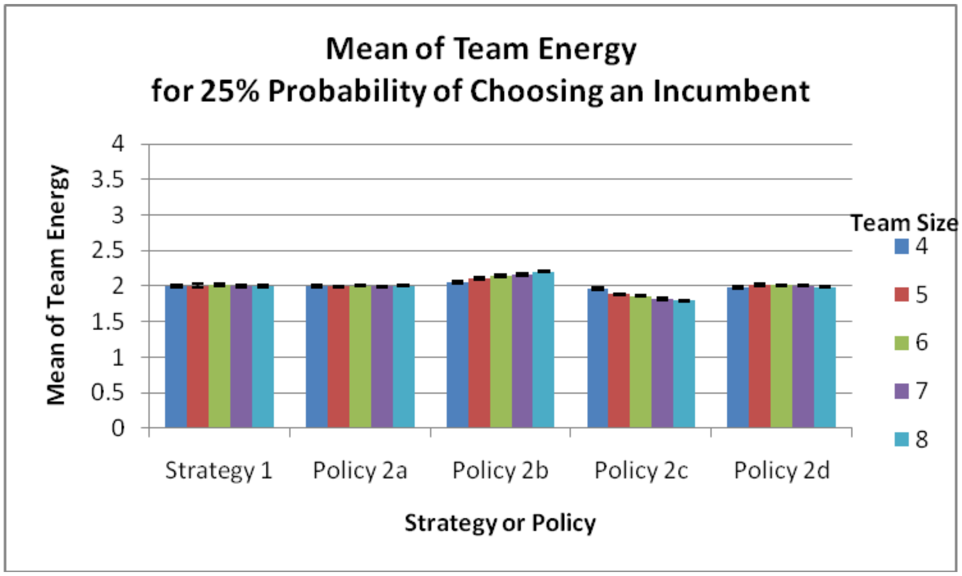

Figure 2: Column graph comparing the mean of team energy for 25% probability of choosing an incumbent with 95% confidence intervals for each strategy and policy for each team size.

Table 7: Standard deviation for mean of team energy for 25% probability of choosing an incumbent for each strategy and policy for each team size.

Standard deviations for 25% probability of choosing an incumbent					
	Team Size				
	4	5	6	7	8
Strategy 1	0.80	0.74	0.68	0.63	0.60
Policy 2a	0.56	0.48	0.43	0.38	0.35
Policy 2b	0.62	0.56	0.53	0.48	0.47
Policy 2c	0.62	0.56	0.52	0.50	0.46
Policy 2d	0.64	0.53	0.48	0.44	0.40

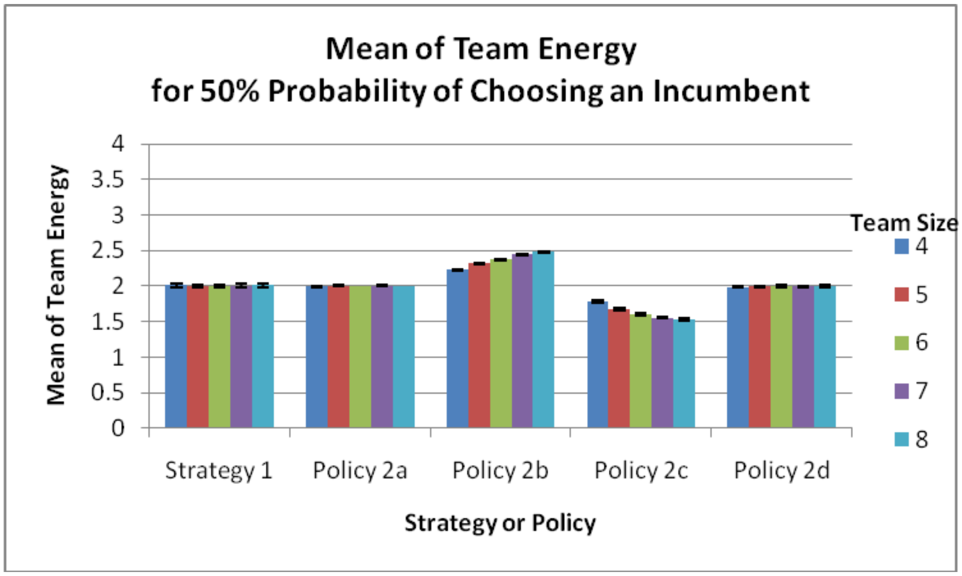

Figure 3: Column graph comparing the mean of team energy for 50% probability of choosing an incumbent with 95% confidence intervals for each strategy and policy for each team size.

Table 8: Standard deviation for mean of team energy for 50% probability of choosing an incumbent for each strategy and policy for each team size.

Standard deviations for 50% probability of choosing an incumbent					
	Team Size				
	4	5	6	7	8
Strategy 1	0.92	0.86	0.80	0.75	0.71
Policy 2a	0.40	0.33	0.28	0.25	0.22
Policy 2b	0.56	0.51	0.48	0.46	0.43
Policy 2c	0.56	0.51	0.48	0.45	0.43
Policy 2d	0.56	0.44	0.38	0.36	0.34

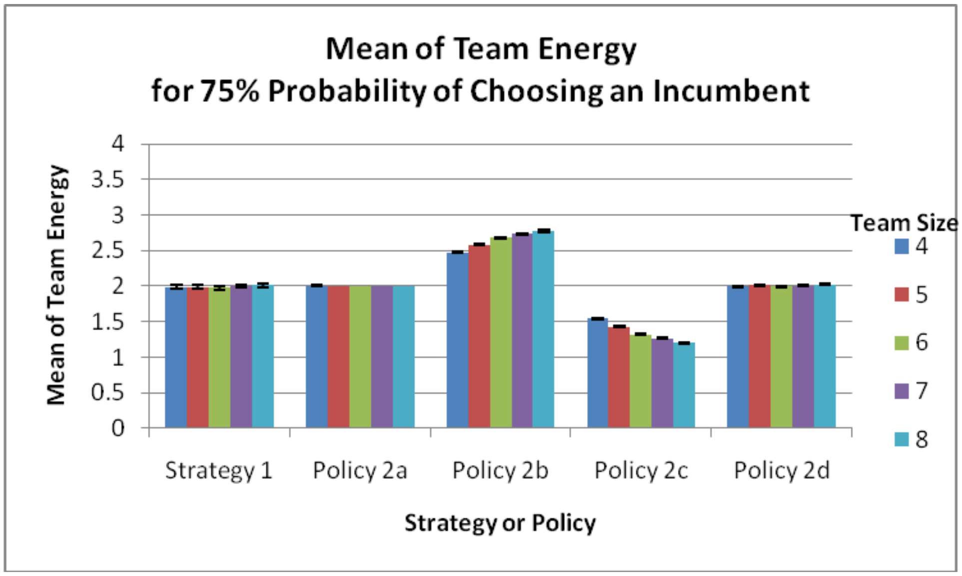

Figure 4: Column graph comparing the mean of team energy for 75% probability of choosing an incumbent with 95% confidence intervals for each strategy and policy for each team size.

Table 9: Standard deviation for mean of team energy for 75% probability of choosing an incumbent for each strategy and policy for each team size.

Standard deviations for 75% probability of choosing an incumbent					
	Team Size				
	4	5	6	7	8
Strategy 1	1.03	0.99	0.95	0.91	0.90
Policy 2a	0.26	0.21	0.17	0.14	0.13
Policy 2b	0.48	0.43	0.39	0.38	0.35
Policy 2c	0.47	0.43	0.40	0.38	0.36
Policy 2d	0.47	0.32	0.29	0.30	0.33

Frequency of Occurrence of Energizing Teams

An energizing team is defined as having a team energy rating greater than or equal to three. The frequency of occurrence of energizing teams divides the number of instances of energizing teams by the total number of teams assembled. The frequency of occurrence of energizing teams for each model parameter combination is graphed in Figures 5 through 7. When the probability of choosing an incumbent is 25% (Figure 5), Strategy 1 has the highest frequency of occurrence of energizing teams regardless of team size. Policy 2b has the second highest frequency of occurrence for team sizes five through eight, while Policy 2d has the second highest frequency for team size four. Strategy 1 and Policy 2b have considerably higher frequencies of occurrence of energizing teams for probabilities of 50% (Figure 6) and 75% (Figure 7) than the other policies. The frequency of occurrence of energizing teams decreases as team size increases regardless of the probability of choosing an incumbent for all of the strategies and policies, except for Policy 2b.

For Strategy 1, smaller team sizes produce higher frequencies of occurrence of energizing teams for each of the three probabilities of choosing an incumbent (Figures 5 through 7). As the probability of choosing an incumbent increases, however, the range of frequencies of occurrence of energizing teams across team sizes decreases. For Policy 2b, the frequency of occurrence of energizing teams decreases as team size increases with a 25% probability of choosing an incumbent (Figure 5), but increases with team size for 50% (Figure 6) and 75% (Figure 7). The frequency of occurrence of an energizing team for Policy 2b is significantly higher that any of the other strategy or policy models for team sizes five through eight when the probability of choosing an incumbent is 75% (Figure 7). Policy 2a, Policy 2c, and Policy 2d each have low frequencies of occurrence of energizing teams. With a 25% probability of choosing an incumbent, each frequency for these three policies is less than 0.1 (Figure 5). By 75% probability, each is less than 0.05 (Figure 7).

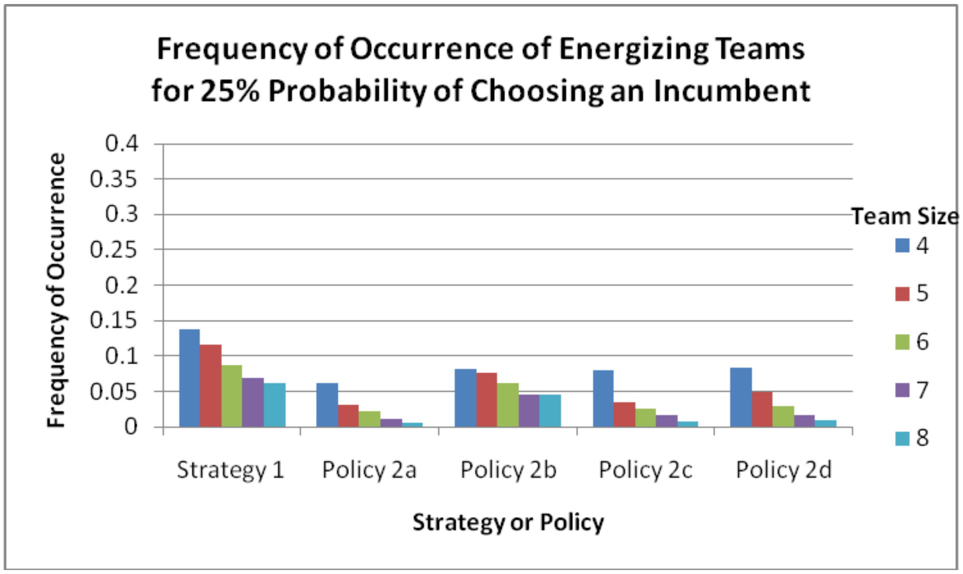

Figure 5: Column graph comparing the frequency of occurrence of energizing teams for 25% probability of choosing an incumbent for each strategy and policy for each team size.

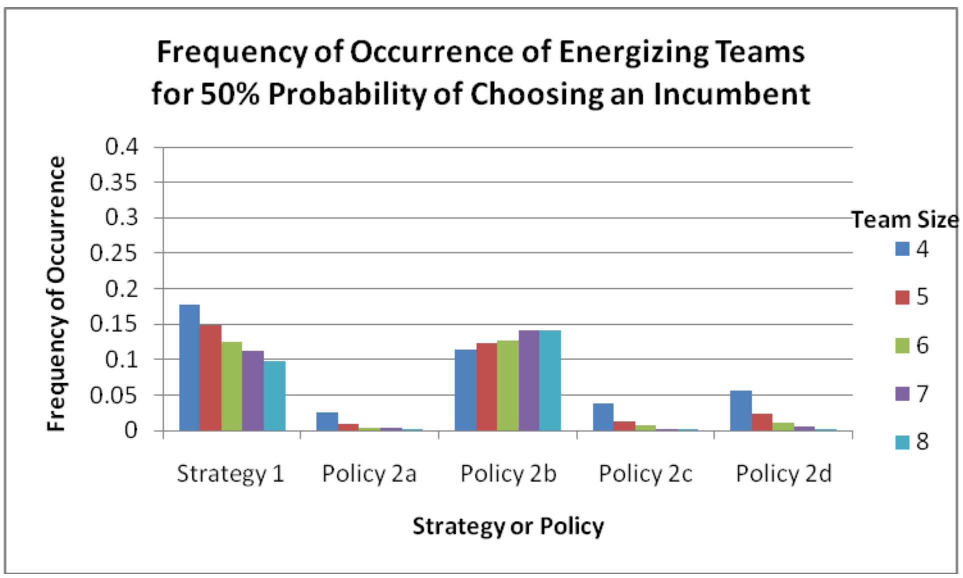

Figure 6: Column graph comparing the frequency of occurrence of energizing teams for 50% probability of choosing an incumbent for each strategy and policy for each team size.

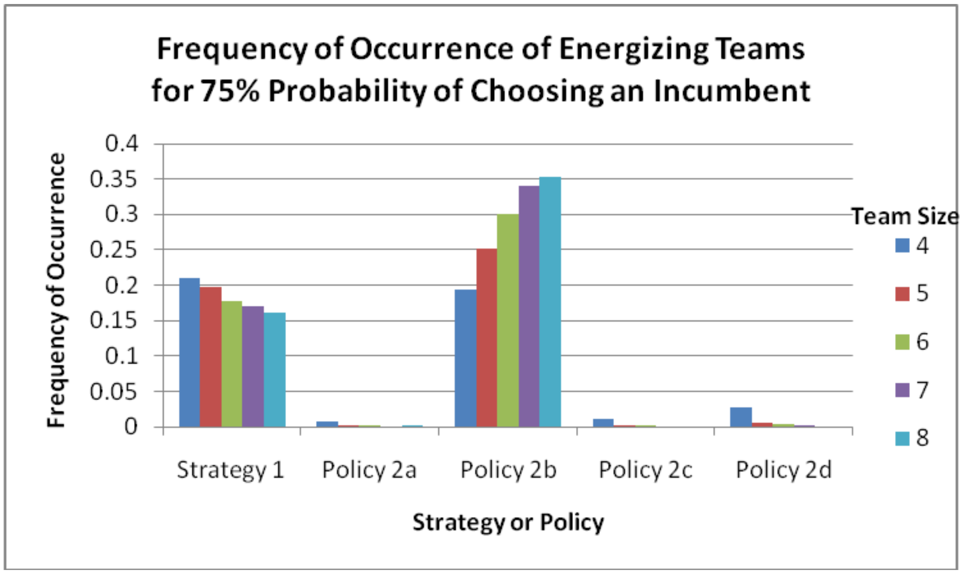

Figure 7: Column graph comparing the frequency of occurrence of energizing teams for 75% probability of choosing an incumbent for each strategy and policy for each team size.

Frequency of Occurrence of De-Energizing Teams

A de-energizing team is defined as having a team energy rating less than or equal to one. The frequency of occurrence of de-energizing teams divides the number of instances of de-energizing teams by the total number of teams assembled. As shown in Figures 8 through 10, Strategy 1 and Policy 2c have considerably higher frequencies of occurrence of de-energizing teams than Policy 2a, Policy 2b, and Policy 2d when the probability of choosing an incumbent is 50% (Figure 9) and 75% (Figure 10). For Policy 2a, Policy 2b, and Policy 2d, the frequency of occurrence of de-energizing teams increases as the team size decreases for each of the three probabilities of choosing an incumbent. Strategy 1 displays this same quality for 25% probability (Figure 8) and 50% probability (Figure 9), but a team size of eight produces a higher frequency of occurrence of de-energizing teams than a team size of seven when the probability of choosing an incumbent is 75% (Figure 10).

For Strategy 1, the frequency of occurrence of de-energizing teams increases with the probability of choosing an incumbent for all team sizes. For Policy 2c, for 25% probability of choosing an incumbent (Figure 8), the frequency of occurrence of energizing teams increases as team size decreases except from team size six to seven for which it is reversed. With a 50% probability of choosing an incumbent (Figure 9), Policy 2c has an almost bell-shaped or slightly negatively skewed distribution across team sizes. For 75% probability of choosing an incumbent (Figure 10), Policy 2c has a steep, increasing amount of difference between frequencies of occurrence across the different team sizes and a significantly higher frequency of occurrence than any of the other strategies and policies.

Policy 2d has a fairly high frequency of occurrence for team size four across the probabilities of choosing an incumbent (Figures 8 through 10), but otherwise Policy 2a, Policy 2b, and Policy 2d all have very low frequencies of occurrence of de-energizing teams. Excluding Policy 2d with team size four, Policy 2a, Policy 2b, and Policy 2d each have less than 0.1 at 25% probability of choosing an incumbent (Figure 8) with less than 0.25 by 75% probability (Figure 10) with most just barely greater than zero.

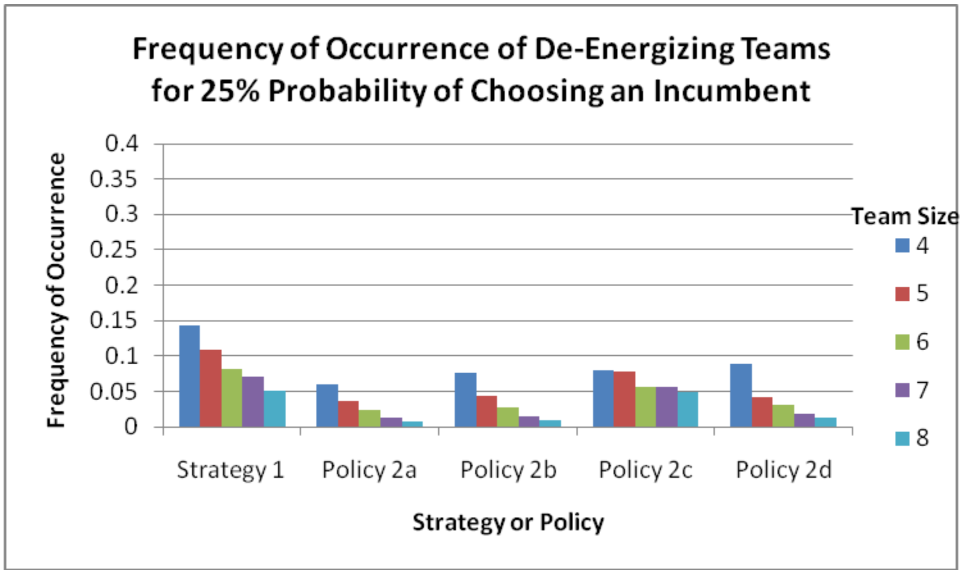

Figure 8: Column graph comparing the frequency of occurrence of de-energizing teams for 25% probability of choosing an incumbent for each strategy and policy for each team size.

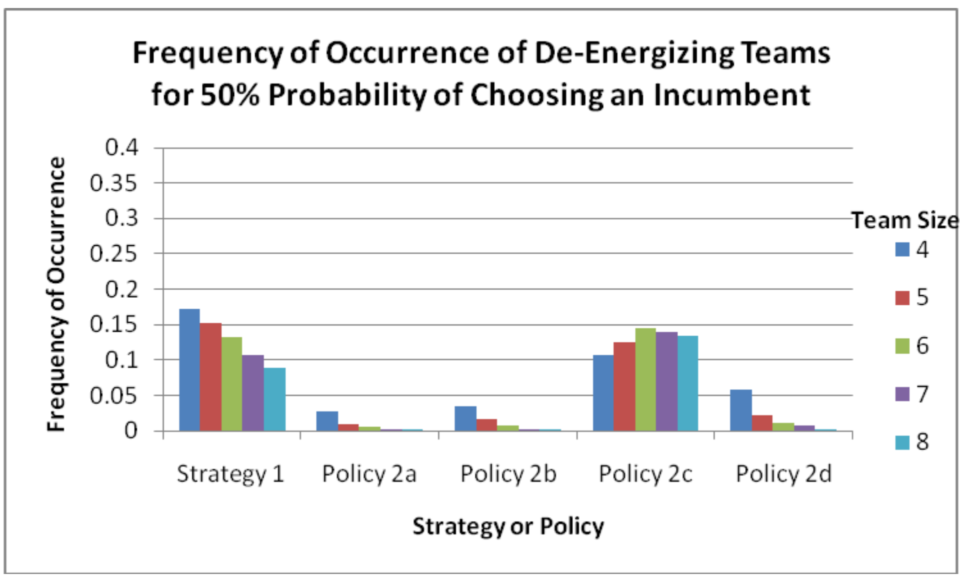

Figure 9: Column graph comparing the frequency of occurrence of de-energizing teams for 50% probability of choosing an incumbent for each strategy and policy for each team size.

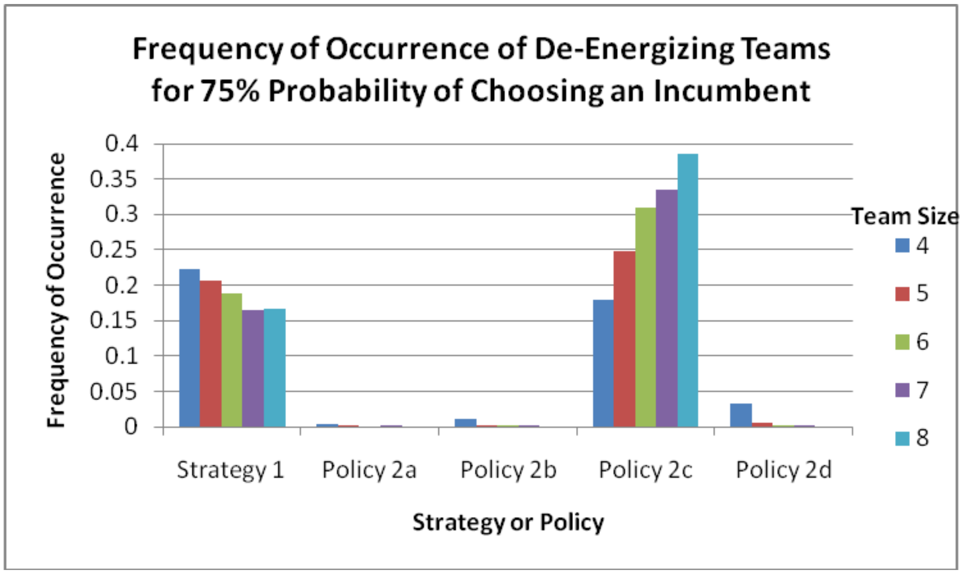

Figure 10: Column graph comparing the frequency of occurrence of de-energizing teams for 75% probability of choosing an incumbent for each strategy and policy for each team size.

Summary

This chapter presented an explanation of the model simulation trials conducted and a description of the results. A total of 26 simulation replications were run for each trial to test each combination of model parameters (team size and the probability of choosing an incumbent) for the different strategies and policies. The results include three major data sets: mean of team energy, the frequency of occurrence of energizing teams, and the frequency of occurrence of de-energizing teams. A discussion of the simulation results and conclusions that can be drawn will be presented in Chapter 6.

Chapter 6: Conclusions

This chapter provides a discussion of the simulation results and conclusions for managers regarding the strategies and policies explored. The analysis and discussion focuses on each strategy, expanding on the results obtained with the simulation runs, explaining why certain results were observed, and determining the scenarios in which each strategy and policy should be implemented. The important findings are summarized in Table 10 at the end of the first section. This chapter also provides proposed extensions of the model and future work related to the area of energy networks in network and agent-based simulation models.

Discussion of Results and Conclusions

Strategy 1:

Strategy 1 allows agents to organize without team composition constraints, but assumes that they will assemble based on similar energy rating. Regardless of team size, Strategy 1 results in the highest frequency of occurrence of energizing teams when the probability of choosing an incumbent is 25%. It results in the highest frequency of occurrence of energizing teams at 50% probability of choosing an incumbent for teams of size four or five and facilitates a high frequency of occurrence of energizing teams at 75% compared to most of the other policies (second to Policy 2b in this regard for all but team size four, for which Strategy 1 has a higher frequency of occurrence of energizing teams).

While the high frequency of occurrence of energizing teams makes Strategy 1 appear to be a good option for obtaining mostly energizing teams, managers must also realize that Strategy 1 has almost identical frequencies of occurrence of de-energizing teams. Strategy 1 results in the highest frequency of occurrence of de-energizing teams when the probability of choosing an incumbent is 25%, regardless of team size. It results in the highest frequency of occurrence of de-energizing teams at 50% probability of choosing an incumbent for teams of size four or five and facilitates a high frequency of occurrence of de-energizing teams at 75% compared to most of the other policies (second to Policy 2c in this regard for all but team size four, for which Strategy 1 has a higher frequency of occurrence of de-energizing teams).

From the simulation results, allowing workers to organize based on similar energy rating appears to result in energizing teams about as frequently as de-energizing teams. Energizing teams result more often with smaller team sizes and a larger probability of choosing an incumbent, but so do de-energizing teams. This causes the mean of team energy to be approximately two for Strategy 1 regardless of the probability of choosing an incumbent or team size. There is a high level of variability in the team energies for this strategy because it is based on the first agent or agents added to a team.

The standard deviation for Strategy 1 increases with the probability of choosing an incumbent. When the first member of a team has an energy rating at one of the extremes (zero or four), that team is more likely to have a final team energy near that initial extreme energy level when the probability of choosing an incumbent is higher. The addition of newcomers, which can have an energy rating dissimilar to the current team energy since newcomers are not subject to the strategy rules, brings the team energy closer to neutral. When the probability of choosing an incumbent is higher, team energy at the extremes stays at the extremes and there is more variability in the resulting team energy, as fewer newcomers are added to teams. If teams in an actual business network appear likely to organize based on similar energy type as in Strategy 1, it appears to be a high risk, high reward strategy over the long-run because the high frequency of energizing teams is offset by the high frequency of de-energizing teams.

Policy 2a:

The intent of Policy 2a is to balance team energy rating when a team is assembled. This is exactly what happens in the simulation results, as a neutral mean of team energy of approximately two occurs regardless of team size or probability of choosing an incumbent. This policy tends to have low standard deviation values for all parameter combinations. This low variability indicates that when managers implement Policy 2a, they are virtually guaranteed of obtaining a team with a neutral energy level, especially as the probability of choosing an incumbent increases.

Policy 2a also ensures a neutral team energy most of the time because it has an extremely low frequency of occurrence of both energizing and de-energizing teams. Policy 2a clearly has the lowest frequency of occurrence of energizing teams of any strategy or policy regardless of the probability of choosing an incumbent. When the probability of choosing an incumbent is 25%, Policy 2a with team size four has a frequency of occurrence of energizing teams greater than 0.05 for the simulations run. The frequency of occurrence of energizing teams is less than 0.05 for every other combination of team size and probability of choosing an incumbent, reaching a nearly non-existent level for large team sizes at 50% and all team sizes at 75%.

Policy 2a also produces the lowest frequency of occurrence of de-energizing teams of any strategy or policy regardless of the probability of choosing an incumbent. Similar to the frequency of occurrence of energizing teams, when the probability of choosing an incumbent is 25%, Policy 2a with team size four has a frequency of occurrence of de-energizing teams greater than 0.05 for the simulations run. The frequency of occurrence of de-energizing teams is less than 0.05 for every other combination of team size and probability of choosing an incumbent, again reaching a nearly non-existent level for large team sizes at 50% and all team sizes at 75%. Managers should only implement Policy 2a when they are sure that neutral-energy teams are the best solution for their organizations, as energizing (or de-energizing) teams will very rarely result with this policy.

Policy 2b:

The constraint Policy 2b implements in the model is to include at least one member with an energy rating less than two per team, but otherwise to select energizing workers. This is a realistic scenario in which managers want to minimize the negative effect that a de-energizer could have on a team by putting them with mostly energizers. In order to realistically opt for this policy, managers need an organization with many energizers or the ability to minimize the inclusion of de-energizers in teams. The second option will often depend on the specific skill sets of energizers and de-energizers in an organization. If an organization has enough energizers that possess the skills needed in teams, minimizing the number of de-energizers in teams would be expected to produce a high frequency of occurrence of energizing teams and the model results confirm this.

The results indicate that energizing teams occur more frequently for Policy 2b with a higher probability of choosing an incumbent. A 25% probability will produce more energizing teams than the other three policies, but less than Strategy 1. This is an unexpected result because the motivation behind Policy 2b focuses on choosing mostly energizers, while Strategy 1 is more variable. It seemed correct to expect that Policy 2b would have a higher frequency of occurrence of energizing teams for 25% probability of choosing an incumbent as it does for 50% and 75%. With a 50% probability of choosing an incumbent, energizing teams result more often in general and especially for larger team sizes. At 75% probability, energizing teams result at a much higher frequency than almost all of the other strategies or policies. A larger team size enhances the frequency of occurrence of energizing teams with Policy 2b at larger probabilities of choosing an incumbent as well. The overall highest frequency of occurrence of energizing teams is approximately 0.39 for Policy 2b with a team size of eight and a 75% probability of choosing an incumbent. To obtain energizing teams frequently, managers should build teams with seven or eight workers and add mostly incumbents to them.

Policy 2b is made more attractive by the fact that there is a rather low probability of obtaining de-energizing teams with it, especially at higher probabilities of choosing an incumbent. This is not surprising given the rules it requires for team composition, but is important to consider when determining whether to use the policy. The chances of avoiding a de-energizing team with a 25% probability of choosing an incumbent are not overwhelming compared to the other strategies and policies, but as the probability of choosing an incumbent increases this frequency of occurrence become almost non-existent. When larger teams assemble at higher probabilities of choosing incumbents, this policy not only increases the frequency of occurrence of energizing teams, but also decreases the frequency of occurrence of de-energizing teams.

The dissimilar frequencies of occurrence of energizing and de-energizing teams explain why the means of team energy for Strategy 1 and Policy 2b are not similar, despite similar frequencies of occurrence of energizing teams at 25% and 50% probability of choosing an incumbent. Policy 2b has much lower frequencies of occurrence of de-energizing teams compared to Strategy 1, which has high frequencies of occurrence of both energizing and de-energizing teams that causes the mean of team energy to balance out at a neutral level. Policy 2b has a much higher frequency of occurrence of energizing teams that skews the mean of team energy over many replications. Managers should use Policy 2b to obtain a higher frequency of energizing teams when there is an abundance of energizers and they want or need to include de-energizers in teams. The means of team energy indicate that team energy will be greater than two for any team size at any probability of choosing an incumbent. As the probability of choosing an incumbent increases so does the mean of team energy for each team size, about a half of an energy rating which is not insignificant for a five-point scale.

Policy 2c:

With Policy 2c, managers want teams with mostly de-energizers to include at least one energizer to raise the energy of the team. This could be a realistic scenario in organizations that do not have an abundance of energizers, where managers want to prevent every team from being composed entirely of de-energizers. It is to be expected that this policy will result in mostly de-energizing teams and this is confirmed by the simulation results. The simulation data indicates that de-energizing teams occur more frequently for Policy 2c with a higher probability of choosing an incumbent. Even when the probability of choosing incumbents is low (25%) and more newcomers are added to teams, Policy 2c produces de-energizing teams more frequently than any of the other policies aside from Strategy 1 and one instance of Policy 2d (when team size is four).

With a 50% probability of choosing an incumbent, de-energizing teams result more often in general and especially for larger team sizes. At 75% probability, de-energizing teams result at a much higher frequency than all of the other models except for Strategy 1 for team size four. Larger team sizes produce a considerably higher frequency of occurrence of de-energizing teams at larger probabilities of choosing an incumbent with Policy 2c, as well. The overall highest single frequency of occurrence of de-energizing teams is approximately 0.35 for Policy 2c with a team size of eight and a 75% probability of choosing an incumbent.

While Strategy 1 produces a higher frequency of de-energizing teams than Policy 2c in many cases, especially at lower probabilities of choosing an incumbent, it still has a mean at approximately two regardless of team size or probability of choosing an incumbent. Conversely, Policy 2c has a mean of team energy less than two regardless of team size or probability of choosing an incumbent. This is explained by the fact that Policy 2c has much lower frequencies of occurrence of energizing teams compared to Strategy 1. High frequencies of occurrence of both energizing and de-energizing teams cause Strategy 1 to balance out its mean of team energy, while Policy 2c has a much higher frequency of occurrence of de-energizing teams that skews the mean of team energy over many replications. As the probability of choosing an incumbent increases, the mean of team energy for Policy 2c decreases for each team size by almost a half of an energy rating. It appears that managers should only implement Policy 2c when they must, using a combination of low probability of choosing an incumbent (25%) and a team size between six and eight.

Policy 2d:

With Policy 2d, managers want a high level of variability in the energy ratings of team members, so at least one team member with each energy rating must be present in a team before incumbents with repeat energy ratings can be added. There are a number of competing dynamics at work with this policy. For teams of five with all incumbents, there will be one member with each energy rating resulting in neutral team energy of two. This is only a single outcome, however, and in most cases newcomers are added to teams without adhering to the policy rules. Furthermore, when team sizes are greater than five (the number of energy ratings), incumbents with repeat energy ratings are added to teams which can shift the mean of team energy. Despite these possibilities, the mean of team energy for Policy 2d is neutral over the course of simulation runs. This result indicates that choosing a member with each energy rating firmly establishes the mean at a neutral energy level so that even when newcomers and workers with repeat energy ratings are added, they usually do not shift it very far from two.

Policy 2d has a noticeably higher frequency of occurrence of both energizing and de-energizing teams when the team size is four regardless of the probability of choosing an incumbent. This could be explained by the fact that team size four means that not every energy rating will be represented in teams and the mean of team energy could be skewed away from the neutral level. This might also be expected when team sizes are larger and teams have more members than there are energy ratings, resulting in repeats that can skew the mean if at the extremes. However, for larger team sizes, the frequency of occurrence of energizing and de-energizing teams is rather low despite the fact that there is a chance for multiple instances of the same energy rating on a team. Overall, the simulation results for Policy 2d are the most difficult to reconcile and a clear recommendation for managers is not apparent.

Table 10 summarizes some of the important conclusions for the strategies and policies modeled.

Table 10: Comparison of conclusions for strategies and policies modeled

Strategy and Policy Conclusions and Recommendations for Managers		
Strategy or Policy	Mean of Team Energy	Manager Recommendation
Strategy 1: Organization based on similar energy rating	Neutral	Use when willing to go for potential high frequency of occurrence of energizing teams at the risk of high frequency of occurrence of de-energizing teams as well
Policy 2a: Balanced team energy	Neutral	Use when willing to practically guarantee teams with neutral energy
Policy 2b: Energizing with at least one de-energizer	Greater than two	Use when there is an abundance of energizers and want or need to include de-energizers
Policy 2c: De-energizing with at least one energizer	Less than two	Use only when composition of network makes it necessary because of de-energizer skills or an abundance of de-energizers
Policy 2d: Distributed variable energy	Neutral	Inconclusive from simulation results

Future Work

In this thesis, an energy component was integrated into a simulation model from an agent perspective, and the simulation results were used to explore various strategies for team assembly that incorporate energy ratings. The simulation model included simplifying assumptions that limited how realistic the framework of team assembly could be. Teams in the model are assembled based entirely on a single factor, a worker’s energy rating. In actual organizations, a number of different characteristics, competencies, and skills are usually considered when assembling teams. For future work, including additional agent variables in the model would likely be valuable to explore because of the more complex and realistic decision-making processes they would facilitate. Energy is just one method for measuring how well people work together and additional attributes could be included for other qualities and competencies to make the decisions about composing teams more realistic. If two agents have the same energy rating, some preference for additional attributes could be used to determine which co-worker to add to the team rather than choosing randomly between them as the model currently does.

Another simplifying assumption is that a given agent's energy rating is considered the same by every other agent in the model. Perception of energy level is subjective and variable in the real world. Furthermore, agents have the same energy rating throughout the entire simulation, which is not consistent with the real world because energy is not a static or permanent characteristic of each person, but rather a dynamic perception that is constantly changing based on how others view that person's energy level in interactions. A person's perception of a co-worker's energy will often evolve in response to each interaction. A model that most accurately represents energy networks in an organization would need to update an agent's energy after each team is assembled or even after each member is added to a team to more precisely represent changes in energy perception as they occur in the real world.

Including a dynamic employee energy component would require every agent in the simulation model to have a personal energy level and a perception of the energy of every other agent in the network. An agent's personal energy level could change during the process of team assembly, based on the energy ratings of the agents it interacts with.

A matrix could be used to store these agent perceptions and after each interaction – whenever a member is added to a team or a complete team is assembled – the matrix would be updated to reflect any changes in an agent's personal energy level or in the perception of energy in others in the network. This methodology might work best in a business network with a set number of people where it could be observed whether the same workers are being added to teams each time step and how individual energy ratings change over time.

A useful extension of the adapted model would be to integrate multiple strategies into a single model so that teams at each time step could have different motivations for team assembly. Another possibility is to incorporate degrees of belief in a strategy, to observe how team assembly behavior and team energy change based on strict and relaxed adherence to a strategy's rules. The probability of choosing a previous collaborator that is used in the baseline model could be included in the adapted model to explore the effects of this parameter on team energy. The team assembly practices of different kinds of companies could also be directly compared with the model by making assumptions about the values of parameters depending on the maturity of the firm (for example, start-up versus established). Any of these extensions can be further enhanced by giving the agents in the adapted model all of the characteristics required to make this an agent-based simulation model. The adapted model provides a solid foundation for future work in team assembly that incorporates energy networks in an agent-based framework.

Modeling and simulation in business cannot be implemented independent of the social context within which it will be conducted. When developing a simulation model, there is a tendency to think that the way to address any perceived deficiencies in it is to add more variables. This perspective is largely taken for the future work section of this thesis because the adapted model is currently limited to a single variable and must be made more realistic before being implemented in an actual business organization. This simulation model is considered an early step in the process of developing an agent-based model that builds on the work done with energy network analysis to provide managers with a tool for assembling effective teams.

As the adapted model becomes more realistic, an assessment of its social implications must also be provided. There are social factors in business networks that cannot be included in simulation models as a model can never be a perfect copy of a system, but only a representation. These factors should be made explicit before implementing the adapted model in a business organization. Furthermore, ethical issues such as the possibility of abuse or manipulation of simulation model to justify controversial decisions or even unjust or prejudiced assessments, movements, or firings must all be addressed. These social context implications are important to consider as the adapted model becomes more realistic and approaches a level of completion where it can be implemented by managers to analyze their business team assembly processes.

Appendix A: Program Code for Strategy 1 Model

The following is the entire program code for the Strategy 1 model:

```
globals
[
  newcomer              ;; an agent who has never collaborated
  component-size        ;; current running size of component being explored
  giant-component-size  ;; size of largest connected component
  components            ;; list of connected components
  average-team-energy   ;; current team's average energy
  energy-list-order     ;; list of team member energy ratings in order added to team
]

turtles-own
[
  incumbent?   ;; true if an agent has collaborated before
  in-team?     ;; true if an agent belongs to the new team being constructed
  downtime     ;; the number of time steps passed since the agent last collaborated
  explored?    ;; used to compute connected components in the graph
  energy       ;; energy rating of each agent
  order-tag    ;; the place a turtle was added to the current team to indicate order
]

links-own
[
  new-collaboration?   ;; true if the link represents the first time two agents collaborated
]

;;;;;;;;;;;;;;;;;;;;;;;;
;;; Setup Procedures ;;;
;;;;;;;;;;;;;;;;;;;;;;;;

to make-newcomer
  create-turtles 1
  [
    set color blue + 1
    set size 1.8
    set incumbent? false
    set in-team? false
    set newcomer self
    set downtime 0
    set explored? false
    set energy random 5
  ]
end
```

```
to setup
  clear-all
  set-default-shape turtles "circle"

  ;; set background patch color to white
  ask patches [set pcolor white]

  ;; assemble the first team
  repeat team-size [ make-newcomer ]
  ask turtles
  [
    set in-team? true
    set incumbent? true
  ]
  tie-collaborators
  color-collaborations

  ask turtles  ;; arrange turtles in a regular polygon
  [
    set heading (360 / team-size) * who
    fd 1.75
    set in-team? false
  ]
  do-plot
end

;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;; Main Procedures ;;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

to go
  ;; all existing turtles are now considered incumbents
  ask turtles [set incumbent? true set color gray - 1.5 set size 0.9]
  ask links [set new-collaboration? false]

  ;; set energy-list-order to an empty list
  set energy-list-order []

  ;; assemble a new team
  pick-team-members
  tie-collaborators
  color-collaborations

  ;; print list of energy ratings for current team
  print energy-list-order
```

```
  ;; age turtles
  ask turtles
  [
    ;; agents drop out of the collaboration network when they are inactive for max-
    ;; downtime steps
    if downtime > max-downtime
      [die]

    set in-team? false
    set downtime downtime + 1
  ]

  if layout? [ layout ]
  if plot? [ do-plot ]
  tick
  ask turtles
  [
    set average-team-energy 0
  ]
end

;; choose turtles to be in a new team
to pick-team-members
  let new-team-member nobody    ;; initially new team member is empty
  let average random 5          ;; sets random initial team energy average to base selection
                                ;; of first incumbent on
  repeat team-size
  [
    ifelse random-float 100.0 >= p       ;; with a probability P, make a newcomer
    [
      make-newcomer
      set new-team-member newcomer
    ]
    [
     ;; if there is already at least one member in team, set average variable to the mean
     ;; energy of the turtle(s) currently in the team
     if any? (turtles with [in-team?]) [set average mean [energy] of turtles with [in-team?]]

     ;; check if there are any incumbents not in team already with energy within 1 energy
     ;; rating (+/-) of the team's current average
     ;; if there are, add one of those incumbents to the team
     ;; otherwise add any available incumbent
     ifelse any? (turtles with [not in-team? and ((average - 1) <= energy) and ((average + 1)
     >= energy)])
        [set new-team-member one-of turtles with [not in-team? and ((average - 1) <=
```

```
        energy) and ((average + 1) >= energy)]]
        [set new-team-member one-of turtles with [not in-team?]]
    ]
    ask new-team-member       ;; specify turtle to become a new team member
    [
      ;; add order tag to keep track of order turtles were added to team
      ifelse count turtles with [in-team?] = 0 [set order-tag 1]
        [ifelse count turtles with [in-team?] = 1 [set order-tag 2]
          [ifelse count turtles with [in-team?] = 2 [set order-tag 3]
            [ifelse count turtles with [in-team?] = 3 [set order-tag 4]
              [ifelse count turtles with [in-team?] = 4 [set order-tag 5]
                [ifelse count turtles with [in-team?] = 5 [set order-tag 6]
                  [ifelse count turtles with [in-team?] = 6 [set order-tag 7]
                    [if count turtles with [in-team?] = 7 [set order-tag 8]]]]]]]]
      set in-team? true
      set downtime 0
      set size 1.8
      set color ifelse-value incumbent? [yellow + 2] [blue + 1]
    ]
    ;; create a new variable to store the energy rating of the newly added team member
    ;; add the new variable to the end of the list that keeps track of (energy-list-order)
    ;; this keeps the energy-list-order variable up-to-date with current team member energy
    ;; ratings in order of when they were added to the team
    let new-energy [energy] of new-team-member
    set energy-list-order lput new-energy energy-list-order
  ]
  ;; updates the average team energy variable with new team member
  set average-team-energy mean [energy] of turtles with [in-team?]
end

;; forms a link between all unconnected turtles with in-team? = true
to tie-collaborators
  ask turtles with [in-team?]
  [
    create-links-with other turtles with [in-team?]
    [
      set new-collaboration? true  ;; specifies newly-formed collaboration between two
                                   ;; members
      set thickness 1              ;; changed to make lines thicker in adapted models
    ]
  ]
end

;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;; Visualization Procedures ;;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
```

```
;; color links according to past experience
to color-collaborations
    ask links with [[in-team?] of end1 and [in-team?] of end2]
    [
      ifelse new-collaboration?
      [
        ifelse ([incumbent?] of end1) and ([incumbent?] of end2)
        [
          set color yellow       ;; both members are incumbents
        ]
        [
          ifelse ([incumbent?] of end1) or ([incumbent?] of end2)
            [ set color green ]  ;; one member is an incumbent
            [ set color blue ]   ;; both members are newcomers
        ]
      ]
      [
        set color black            ;; members are previous collaborators
      ]
    ]
end

;; perform spring layout on all turtles and links
to layout
  repeat 12 [
    layout-spring turtles links 0.18 0.01 1.2
    display
  ]
end

to do-plot
  ;; plot stacked histogram of link types
  set-current-plot "Link counts"
  let total 0
  set-current-plot-pen "previous collaborators"
  plot-pen-up plotxy ticks total
  set total total + count links with [color = black]
  plot-pen-down plotxy ticks total
  set-current-plot-pen "incumbent-incumbent"
  plot-pen-up plotxy ticks total
  set total total + count links with [color = yellow]
  plot-pen-down plotxy ticks total
  set-current-plot-pen "newcomer-incumbent"
  plot-pen-up plotxy ticks total
  set total total + count links with [color = green]
```

```
  plot-pen-down plotxy ticks total
  set-current-plot-pen "newcomer-newcomer"
  plot-pen-up plotxy ticks total
  set total total + count links with [color = blue]
  plot-pen-down plotxy ticks total

  ;; plot a histogram of the number of agents with each energy rating
  set-current-plot "Energy ratings"
  set-plot-y-range 0 count turtles
  set-histogram-num-bars 5
  histogram [energy] of turtles          ;; using the default plot pen

  ;; plot the average team energy of the team assembled at each time step
  set-current-plot "Average Team Energy Over Time"
  plotxy ticks (average-team-energy)     ;; plots average energy of most recent team

end
```

Appendix B: Program Code for Policy 2a Model

The program code for the Policy 2a model is identical to the program code for Strategy 1 found in Appendix A with the exception of the "pick-team-members" command that provides the various rules for choosing agents to teams. The following is the program code for just the "pick-team-members" command for the Policy 2a model.

```
;; choose turtles to be in a new team
to pick-team-members
  let new-team-member nobody    ;; initially new team member is empty
  let average random 5          ;; sets random initial team energy average to base selection
                                ;; of first incumbent on
  repeat team-size
  [
    ifelse random-float 100.0 >= p       ;; with a probability P, make a newcomer
    [
      make-newcomer
      set new-team-member newcomer
    ]
    [
     ;; if there is already at least one member in team, set average variable to the mean
     ;; energy of the turtle(s) currently in the team
     if any? (turtles with [in-team?]) [set average mean [energy] of turtles with [in-team?]]

     ;; if the team energy average is greater than 2, check if there are any incumbents not in
     ;; team with energy < 2
     ;; if there are, add one of them to the team
     ;; if there are not, check if there are any incumbents not in team with energy = 2
     ;; if there are, add one of them to the team
     ;; if there are not, add any incumbent to the team
     ifelse average > 2 [ifelse any? (turtles with [not in-team? and energy < 2])
       [set new-team-member one-of turtles with [not in-team? and energy < 2]]
       [ifelse any? (turtles with [not in-team? and energy = 2])
         [set new-team-member one-of turtles with [not in-team? and energy = 2]]
         [set new-team-member one-of turtles with [not in-team?]]]]

     ;; if the team energy average is less than 2, check if there are any incumbents not in
     ;; team with energy > 2
     ;; if there are, add one of them to the team
     ;; if there are not, check if there are any incumbents not in team with energy = 2
     ;; if there are, add one of them to the team
     ;; if there are not, add any incumbent to the team
     [ifelse average < 2 [ifelse any? (turtles with [not in-team? and energy > 2])
       [set new-team-member one-of turtles with [not in-team? and energy > 2]]
       [ifelse any? (turtles with [not in-team? and energy = 2])
         [set new-team-member one-of turtles with [not in-team? and energy = 2]]
```

```
        [set new-team-member one-of turtles with [not in-team?]]]]

   ;; if the team energy average is equal to 2, check if there are any incumbents not in
   ;; team with energy = 2
   ;; if there are, add one of them to the team
   ;; if there are not, add any incumbent to the team
   [if average = 2 [ifelse any? (turtles with [not in-team? and energy = 2])
      [set new-team-member one-of turtles with [not in-team? and energy = 2]]
      [set new-team-member one-of turtles with [not in-team?]]]]
    ]
   ]
   ask new-team-member                  ;; specify turtle to become a new team member
   [
     ifelse count turtles with [in-team?] = 0 [set order-tag 1]
       [ifelse count turtles with [in-team?] = 1 [set order-tag 2]
         [ifelse count turtles with [in-team?] = 2 [set order-tag 3]
           [ifelse count turtles with [in-team?] = 3 [set order-tag 4]
             [ifelse count turtles with [in-team?] = 4 [set order-tag 5]
               [ifelse count turtles with [in-team?] = 5 [set order-tag 6]
                 [ifelse count turtles with [in-team?] = 6 [set order-tag 7]
                   [if count turtles with [in-team?] = 7 [set order-tag 8]]]]]]]]
     set in-team? true
     set downtime 0
     set size 1.8
     set color ifelse-value incumbent? [yellow + 2] [blue + 1]
   ]

   ;; create a new variable to store the energy rating of the newly added team member
   ;; add the new variable to the end of the list that keeps track of (energy-list-order)
   ;; this keeps the energy-list-order variable up-to-date with current team member energy
   ;; ratings in order of when they were added to the team
   let new-energy [energy] of new-team-member
   set energy-list-order lput new-energy energy-list-order
  ]
  ;; updates the average team energy variable with new team member
  set average-team-energy mean [energy] of turtles with [in-team?]
end
```

Appendix C: Program Code for Policy 2b Model

The program code for the Policy 2b model is identical to the program code for Strategy 1 found in Appendix A with the exception of the “pick-team-members” command that provides the various rules for choosing agents to teams. The following is the program code for just the “pick-team-members” command for the Policy 2b model.

```
;; choose turtles to be in a new team
to pick-team-members
  let new-team-member nobody    ;; initially new team member is empty
  let average random 5          ;; sets random initial team energy average to base selection
                                ;; of first incumbent on
  repeat team-size
  [
    ifelse random-float 100.0 >= p      ;; with a probability P, make a newcomer
    [
      make-newcomer
      set new-team-member newcomer
    ]
    [
     ;; if there is at least one turtle on the team with below average energy (energy < 2)
     ;; add incumbents with energy > 2 if there are any, otherwise add incumbents with
     ;; energy = 2 if there are any
     ;; otherwise add any available incumbents
     ;; else if there are no turtles on the team with below average energy (energy < 2)
     ;; add incumbent with energy < 2 if there are any
     ;; otherwise add incumbent with energy > 2 if there are any
     ;; otherwise add incumbent with energy = 2 if there are any
     ;; otherwise add any available incumbents
     ifelse any? (turtles with [in-team? and energy < 2])
       [ifelse any? (turtles with [not in-team? and energy > 2])
         [set new-team-member one-of turtles with [not in-team? and energy > 2]]
         [ifelse any? (turtles with [not in-team? and energy = 2])
           [set new-team-member one-of turtles with [not in-team? and energy = 2]]
           [set new-team-member one-of turtles with [not in-team?]]]]
       [ifelse any? (turtles with [not in-team? and energy < 2])
         [set new-team-member one-of turtles with [not in-team? and energy < 2]]
         [ifelse any? (turtles with [not in-team? and energy > 2])
           [set new-team-member one-of turtles with [not in-team? and energy > 2]]
           [ifelse any? (turtles with [not in-team? and energy = 2])
             [set new-team-member one-of turtles with [not in-team? and energy = 2]]
             [set new-team-member one-of turtles with [not in-team?]]]]]
     ]

    ask new-team-member                 ;; specify turtle to become a new team member
    [
```

```
    ;; add order tag to keep track of order turtles were added to team
    ifelse count turtles with [in-team?] = 0 [set order-tag 1]
      [ifelse count turtles with [in-team?] = 1 [set order-tag 2]
        [ifelse count turtles with [in-team?] = 2 [set order-tag 3]
          [ifelse count turtles with [in-team?] = 3 [set order-tag 4]
            [ifelse count turtles with [in-team?] = 4 [set order-tag 5]
              [ifelse count turtles with [in-team?] = 5 [set order-tag 6]
                [ifelse count turtles with [in-team?] = 6 [set order-tag 7]
                  [if count turtles with [in-team?] = 7 [set order-tag 8]]]]]]]]
    set in-team? true
    set downtime 0
    set size 1.8
    set color ifelse-value incumbent? [yellow + 2] [blue + 1]
   ]

   ;; create a new variable to store the energy rating of the newly added team member
   ;; add the new variable to the end of the list that keeps track of (energy-list-order)
   ;; this keeps the energy-list-order variable up-to-date with current team member energy
   ;; ratings in order of when they were added to the team
   let new-energy [energy] of new-team-member
   set energy-list-order lput new-energy energy-list-order
  ]
  ;; updates the average team energy variable with new team member
  set average-team-energy mean [energy] of turtles with [in-team?]
end
```

Appendix D: Program Code for Policy 2c Model

The program code for the Policy 2c model is identical to the program code for Strategy 1 found in Appendix A with the exception of the "pick-team-members" command that provides the various rules for choosing agents to teams. The following is the program code for just the "pick-team-members" command for the Policy 2c model.

```
;; choose turtles to be in a new team
to pick-team-members
  let new-team-member nobody    ;; initially new team member is empty
  let average random 5          ;; sets random initial team energy average to base selection
                                ;; of first incumbent on
  repeat team-size
  [
    ifelse random-float 100.0 >= p      ;; with a probability P, make a newcomer
    [
      make-newcomer
      set new-team-member newcomer
    ]
    [
     ;; if there is at least one turtle on the team with above average energy (energy > 2)
     ;; add incumbents with energy < 2 if there are any, otherwise add incumbents with
     ;; energy = 2 if there are any
     ;; otherwise add any available incumbents
     ;; else if there are no turtles on the team with above average energy (energy > 2)
     ;; add incumbent with energy > 2 if there are any
     ;; otherwise add incumbent with energy < 2 if there are any
     ;; otherwise add incumbent with energy = 2 if there are any
     ;; otherwise add any available incumbents
     ifelse any? (turtles with [in-team? and energy > 2])
       [ifelse any? (turtles with [not in-team? and energy < 2])
         [set new-team-member one-of turtles with [not in-team? and energy < 2]]
         [ifelse any? (turtles with [not in-team? and energy = 2])
           [set new-team-member one-of turtles with [not in-team? and energy = 2]]
           [set new-team-member one-of turtles with [not in-team?]]]]
       [ifelse any? (turtles with [not in-team? and energy > 2])
         [set new-team-member one-of turtles with [not in-team? and energy > 2]]
         [ifelse any? (turtles with [not in-team? and energy < 2])
           [set new-team-member one-of turtles with [not in-team? and energy < 2]]
           [ifelse any? (turtles with [not in-team? and energy = 2])
             [set new-team-member one-of turtles with [not in-team? and energy = 2]]
             [set new-team-member one-of turtles with [not in-team?]]]]]
     ]

    ask new-team-member                 ;; specify turtle to become a new team member
    [
```

```
    ;; add order tag to keep track of order turtles were added to team
    ifelse count turtles with [in-team?] = 0 [set order-tag 1]
     [ifelse count turtles with [in-team?] = 1 [set order-tag 2]
      [ifelse count turtles with [in-team?] = 2 [set order-tag 3]
       [ifelse count turtles with [in-team?] = 3 [set order-tag 4]
        [ifelse count turtles with [in-team?] = 4 [set order-tag 5]
         [ifelse count turtles with [in-team?] = 5 [set order-tag 6]
          [ifelse count turtles with [in-team?] = 6 [set order-tag 7]
           [if count turtles with [in-team?] = 7 [set order-tag 8]]]]]]]]
    set in-team? true
    set downtime 0
    set size 1.8
    set color ifelse-value incumbent? [yellow + 2] [blue + 1]
   ]

   ;; create a new variable to store the energy rating of the newly added team member
   ;; add the new variable to the end of the list that keeps track of (energy-list-order)
   ;; this keeps the energy-list-order variable up-to-date with current team member energy
   ;; ratings in order of when they were added to the team
   let new-energy [energy] of new-team-member
   set energy-list-order lput new-energy energy-list-order
  ]
  ;; updates the average team energy variable with new team member
  set average-team-energy mean [energy] of turtles with [in-team?]
end
```

Appendix E: Program Code for Policy 2d Model

The program code for the Policy 2d model is identical to the program code for Strategy 1 found in Appendix A with the exception of the "pick-team-members" command that provides the various rules for choosing agents to teams. The following is the program code for just the "pick-team-members" command for the Policy 2d model.

```
;; choose turtles to be in a new team
to pick-team-members
  let new-team-member nobody    ;; initially new team member is empty
  let average random 5          ;; sets random initial team energy average to base selection
                                ;; of first incumbent on
  repeat team-size
  [
    ifelse random-float 100.0 >= p      ;; with a probability P, make a newcomer
    [
      make-newcomer
      set new-team-member newcomer
    ]
    [
     ;; create a list to keep track of the energy ratings of team members
     let energy-list [energy] of turtles with [in-team?]

     ;; Incumbents will only be added to the team if there is not already an agent in the
     ;; team with the same energy rating
     ;; Check if there are any agents that have energy ratings that are not already present in
     ;; the team
     ;; if there are, add one of them to the team
     ;; otherwise add any incumbent to the team
     ifelse any? (turtles with [not in-team? and not member? energy energy-list])
       [set new-team-member one-of turtles with [not in-team? and not member? energy
energy-list]]
       [set new-team-member one-of turtles with [not in-team?]]
    ]
    ask new-team-member                 ;; specify turtle to become a new team member
    [
      ;; add order tag to keep track of order turtles were added to team
      ifelse count turtles with [in-team?] = 0 [set order-tag 1]
        [ifelse count turtles with [in-team?] = 1 [set order-tag 2]
          [ifelse count turtles with [in-team?] = 2 [set order-tag 3]
            [ifelse count turtles with [in-team?] = 3 [set order-tag 4]
              [ifelse count turtles with [in-team?] = 4 [set order-tag 5]
                [ifelse count turtles with [in-team?] = 5 [set order-tag 6]
                  [ifelse count turtles with [in-team?] = 6 [set order-tag 7]
                    [if count turtles with [in-team?] = 7 [set order-tag 8]]]]]]]]
      set in-team? true
```

```
      set downtime 0
      set size 1.8
      set color ifelse-value incumbent? [yellow + 2] [blue + 1]
    ]

    ;; create a new variable to store the energy rating of the newly added team member
    ;; add the new variable to the end of the list that keeps track of (energy-list-order)
    ;; this keeps the energy-list-order variable up-to-date with current team member energy
    ;; ratings in order of when they were added to the team
    let new-energy [energy] of new-team-member
    set energy-list-order lput new-energy energy-list-order
  ]
  ;; updates the average team energy variable with new team member
  set average-team-energy mean [energy] of turtles with [in-team?]
end
```

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